USING FERMAT NUMBER TRANSFORM
ON TMS320C30 DIGITAL
SIGNAL PROCESSOR
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## AN IMPLEMENTATION OF DIGITAL FILTERS USING FERMAT NUMBER TRANSFORM <br> ON TMS320C30 DIGITAL SIGNAL PROCESSOR

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## PREFACE

Precise systems design, equipment standardization, and stability of performance characteristics are among the many advantages digital techniques can offer in signal processing. Earlier research in this field of study has contributed much to many of the modern day conveniences. Many of these contributions focus on improving computational efficiency of discrete Fourier transform (DFT) calculation. However, there are many shortcomings; therefore number theoretic transform (NTT) is proposed.

This study implements three digital filters using one of the NTT, namely the Fermat number transform (FNT), and DFT. It compares the execution time, number of operation, and memory requirement for both implementations. Implementation of both types of filters employs the radix-2 fast Fourier transform (FFT). This study proposes a modified diminished-one number system in implementing FNT. The number system was originally proposed by Leibowitz.

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## NOMENCLATURE

| CCP | cyclic convolution property |
| :--- | :--- |
| DFT | discrete Fourier transform |
| DIF | decimation-in-frequency |
| DIT | decimation-in-time |
| DSP | discrete signal processor |
| EVM | evaluation module |
| FFT | fast Fourier transform |
| FNT | inverse discrete Fourier transform |
| IDFT | inverse Fermat number transform |
| IFNT | Mersenne number transform |
| MNT | number theoretic transform |
| NTT | prime factor algorithm |
| PFA | Rader transform |
| RT | Texas Instruments |
| TI | Winograd Fourier transform algorithm |
| WFTA |  |

## CHAPTER 1

## 1. INTRODUCTION

C.M. Rader introduced Mersenne number transform (MNT) in 1972 [1]. His proposal started a whole new category of transform, generally termed as number theoretic transform (NTT). This opened up new possibilities in digital signal processing. Among the many claims of number theoretic transform are precision and accuracy, processing speed, and a lower memory requirement compared to its complex counterpart. As the structure of NTT is very similar to that of DFT, FFT algorithms are most suitable for improving efficiency. Interesting enough, FFT algorithms did not draw much attention until a decade earlier, when Cooley and Tukey published their paper in 1965 [2].

This study seeks to implement lowpass, bandpass, and highpass filters using NTT and DFT. The specific focus is FNT and DFT, using radix-2 FFT algorithm implementations. The software Hypersignal was used to design the filters, producing a set of filter data sequence to convolute with input signals. A modification of L.M. Leibowitz's diminished-one number system used to implement FNT is presented. The study compares the execution time and the memory requirement for the two implementations. An analysis
of the computational accuracy is also presented. All these implementations are run on Texas Instruments' (TI) TMS320C30 evaluation module.

Chapter 2 contains a historical account of the development of the field of digital signal processing. The chapter first recount early 19th century discoveries. A description of the improvements in both NTT and DFT will follow. Chapter 3 gives the necessary background information regarding the implementations in this study. Chapter 4 discusses the specific implementations. A detailed description of the algorithm implemented in this study, followed by a discussion of the modified diminishedone operations is also presented. Chapter 5 presents an analysis of the results collected from the two implementations. This paper will then end with a summary in chapter 6. It reiterates the findings and wraps up this study.

## CHAPTER 2

## 2. LITERATURE REVIEW

### 2.1 Introduction

The contribution of the French mathematician Jean Baptiste Joseph Fourier (1768 - 1830) is a major milestone to the study of signal processing [3]. Fourier first demonstrated the method of representing periodic functions in infinite harmonic series. This method, now known as the Fourier series, has become a valuable tool for the study of digital signal processing. Later, the definition of the Fourier transform is developed from the foundation of this work. Just as the Fourier series describes a periodic function in terms of the frequency-domain attributes of amplitude and phase, the Fourier transform extends this frequency-domain description to aperiodic functions.

However, digital signal processing did not catch on until Cooley and Tukey published their work in 1965 [2]. Their work was indeed a turning point in digital signal processing and in certain areas of numerical analysis. With their method, the order of complexity of performing DFT drops from $O\left(N^{2}\right)$ to a significantly lower order at $O\left(N \log _{2} N\right)$.

Less known to many researchers, however, is the treatise written by the eminent German mathematician Carl Friedrich Gauss (1777-1855) [4]. This treatise described an algorithm similar to the Cooley-Tukey FFT more than one hundred and fifty years earlier, in 1805. As noted by $H$. Burkhardt [5] in 1904 and H. H. Goldstine [6] in 1977, this work predated even Fourier's 1807 work on harmonic analysis.

Although DFT is useful in today's digital electronic era, time-consuming complex operations and roundoff errors due to finite word length plague its usefulness. Many researchers have begun to explore similar transforms exhibiting cyclic convolution property (CCP), which is having the transform of the cyclic convolution of two sequences equal to the product of their transforms. In 1971, Pollard published a paper [18] discussing the conditions for having transforms showing CCP and defined transforms in a finite (Galois) field. Transforms in the rings of integers appeared after Rader proposed the transforms in the rings of integers modulo a Mersenne number or a Fermat number. Researchers call these transforms in a ring of integers NTT.

This chapter first recounts the development behind modern day digital signal processing since early 1800. Then, an account of the progress in DFT follows. Thereafter, the chapter discusses progress in NTT.

### 2.2 Theoretical Development

### 2.2.1 Early Developments

In a well-documented article [7], M.T. Heideman referred to two earlier papers [5,6], confirming Gauss's contribution to the study of signal processing. He quoted Herman H. Goldstine [6], "This fascinating work of Gauss was neglected and was rediscovered by Cooley and Tukey in an important paper in 1965." Here, he was referring to Gauss's treatise, "Theoria Interpolations Methodo Nova Tractata." Gauss published this treatise, most likely written in 1805, in 1866. H. Burkhardt, who wrote in 1904 [5], also noted the contribution of Guass.

While a student at Göttingen, Gauss became familiar with the works of Leonhard Euler (1707-1783) and Joseph Louis Lagrange (1736-1813) on the analysis of trigonometric series [7]. He later extended these works on trigonometric interpolation to periodic functions. Nevertheless, most of his important publications are in a nineteenth-century version of Latin, called neo-Latin. Unfortunately, it is difficult for a casual student of classical Latin to translate neo-Latin accurately. Gauss's notation in describing his method also posts an obstacle to modern readers. As such, his work went largely unnoticed. Heideman wrote, "Burkhardt pointed out this algorithm in

1904 and Goldstine suggested the connection between Gauss and the FFT in 1977, but both of these went largely unnoticed, presumably because they were published in books dealing primarily with history." So, the world did not benefit from Gauss's method until Cooley and Tukey came along in 1965.
"Gauss's algorithm is as general and powerful as the Cooley-Tukey common-factor algorithm and is, in fact, equivalent to a decimation-in-frequency algorithm adapted to a real data sequence," wrote Heideman. Although Gauss did not go on to quantify the computational requirements of his method, clearly his algorithm performs in the order of complexity at the now familiar $O\left(N \log _{2} N\right)$.

Although Gauss's contribution precedes that of Fourier, Fourier's work in harmonic series commands more attention. It is fascinating to see that the knowledge acquired in one field of study became useful in another. In fact, Fourier was studying and analyzing the heat flow in metal rods when he discovered the trigonometric series representation of a periodic function. He did not know the importance of his work to modern day signal processing. Essentially, Fourier showed that any periodic function is expressible as a function of harmonic frequencies of the fundamental frequency, which we now refer to as the Fourier series. Such mathematical abstraction of periodic functions is a
useful tool for objective observation of periodic signals. Beside the physical interpretation to view periodic functions as a sum of component functions with harmonic frequencies, Fourier series allow us to describe such functions in their frequency-domain attributes. Further development introduces the idea of Fourier transform, giving us the abstract mathematical tools to study aperiodic functions.

Over the years, independent works that were unrelated to Gauss's work appeared, but were not as general or as well formulated as his work. Many of the methods did not handle computation above the fourth harmonics until Runge published his work [7] in the early 1900's.

### 2.2.2 Discrete Fourier Transform

At the turn of the century, Runge proposed an algorithm for lengths equal to powers of two [7], which was later generalized to powers of three as well. Apparently, his work was well known and was cited in the popular textbook written by Whittaker and Robinson [8]. His influence did not survive after the war, however.

After the war, in 1958, another important contribution appeared. Good developed an index mapping that facilitated the division of a problem into subproblems of smaller length [9]. This mapping itself is an application of the Chinese
remainder theorem, which dates back to the Chinese mathematician Sun-Tsu some time between 200 BC and 200 AD [10]. When Cooley and Tukey presented their fast Fourier transform in 1965, they claimed to base their work on Good's mapping, apparently unaware of Gauss's algorithm that the world had forgotten more than a century ago. However, there are major differences between Good's algorithm and the Cooley-Tukey FFT. The former does not require auxiliary complex multiplications, referred to as twiddle factors, while the later does; thus, the two different classes of FFT.

The development of FFT, without twiddle factors, did not become popular with Good's algorithm, which is suitable when factors of the transform length are coprime, or are indivisible by each other. Good's algorithm requires a set of efficient small-length DFT algorithms. Paradoxically, in 1968, Rader published a paper that showed how to map a prime length $N$ DFT into circular convolution of length $N-1$ [11]. Yet, not until Winograd's study on complexity theory [12] that the two foundation works above are ready for efficient applications on signal processing. Winograd published his paper in 1977, presenting his complex theory, particularly on the number of multiplications required for computing polynomial products or convolution. His work is crucial to this class of FFT. With Good's mapping, coupled with

Rader's fast convolution scheme, a first algorithm makes use of the intimate structure of these convolution schemes to obtain a nesting of the various multiplications. This algorithm is now known as Winograd Fourier transform algorithm (WFTA). If the nesting is not used, the resulting algorithm is known as prime factor algorithm (PFA).

The development in FFT with twiddle factors took off with the Cooley-Tukey FFT. Unlike Good's algorithm, the Cooley-Tukey FFT can have transform length of any composite length. With the growing interest in the theoretical aspects of digital signal processing motivated by technical improvements in the semiconductor industry, and the availability of reasonable computing power, the Cooley-Tukey FFT quickly became an interest of research. They employ the divide and conquer approach by separating input sequences to process. When the sequence length is a power of two, their algorithm becomes what is known as the radix-2 decimation-in-time (DIT) algorithm. Emphasis on a dual approach leads to decimation-in-frequency (DIF) algorithm. Later, Bergland noted that the algorithm can be more efficient with higher radices like radix-8 [13]. In 1984, there were four proposals $[14,15,16,17]$ submitted at about the same time that leads to split-radix algorithm. This approach uses a different radix for the even part (radix-2) and the odd part (radix-4).

This research uses a radix-2 algorithm for comparison with the NTT implementation. Thus, it is the author's intention to leave the rest of the development in this thread, for example polynomial transform, to the reader to explore. This discussion will continue with the motivations and history of NTT.

### 2.2.3 Number Theoretic Transform

In his paper published in 1971 [18], J.M. Pollard defined a transform in finite (Galois) field analogous to the DFT. Replacing the complex roots of unity in DFT with $r^{k}$, where $r$ is a member of any field $F$, of order $d$ and $k$ is an integer, he showed that CCP holds for the transform in $F$. This is under the condition that $r$ has finite order $d$ in the multiplicative group $F^{*}$ of $F$. Generalizing his definition, he suggested transforms in a ring of integers modulo $m$, where $m$ is an integer. C.M. Rader picked up from here and introduced a transformation defined in the rings of integers modulo a Mersenne number [1]. We now call this transform Mersenne number transform (MNT).

Unlike DFT, the only arithmetic operations MNT needs are that of additions and circular shifts of bits within a word. One other advantage the MNT has over DFT is the accuracy of the transformation it can attain; virtually no
roundoff errors. Rader also suggested a transformation using Fermat numbers. In time, researchers coined the term 'number theoretic transform' to refer to similar transformations. Later in 1974, R.C. Argarwal and C.S. Burrus [19] worked on a transform using Fermat numbers, named Fermat number transforms (FNT). In their paper, they formalized the conditions for $\operatorname{CCP}$ and showed its relation to the transform length. Unlike Rader, they defined the roots of unity as $\alpha^{r}$ instead of $2^{r}$. Thus giving more flexibility to the transform. Since these transformations are similar to the DFT, therefore FFT algorithms are perfectly suitable on NTT to achieve better efficiency. As the topic of interest is on implementation of FNT, many of the later developments in NTT are left to the readers to explore. The emphasis will now turn to issues in the implementation of FNT.

Argarwal and Burrus proposed implementations of the various basic arithmetic operations modulo a Fermat number, $F_{t}=2^{b}+1$, in their paper [19]. However, this method does not have the convenience of circular shifts of bits when performing scaling. The method also involves the representation of the number -1 , requiring $b+1$ bits. The integer $b$ is equal to $2^{t}$. Argarwal and Burrus decided to ignore this extra bit in order to simplify modular arithmetic operations. While McClellan developed a
technique of exact computation using a new binary code representation of $b+1$ bits in 1976 [20], L.M. Leibowitz proposed a similar binary representation he called diminished-one number system the same year [21]. His method shows less mathematical complexity than that of McClellan. It also allows circular bit shifts for scaling by powers of 2. This paper builds on the foundation of Leibowitz's diminished-one number system and presents modifications to the various diminished-one number operations.

### 2.3 Hardware Environment

### 2.3.1 TMS320C30 Evaluation Module

The TMS320C30 Evaluation Module (EVM) is a tool for application development. This module allows the execution and debugging of application programs. With one of the fastest digital signal processors (DSP), the 33-MFLOP TMS320C30 floating-point DSP, this EVM provides a lot of computing power. This section will give a brief description of the hardware environment used in this study.

As mentioned earlier, the TMS320C30 EVM employs the TI TMS320C30 DSP for its brain power. This DSP has a 60-ns single-cycle instruction execution time (33Mhz). The processor has one $4 \mathrm{~K} \times 32$-bit single-cycle, dual-access onchip ROM block, and two 1 K x 32 -bit single-cycle dual-access
on-chip RAM blocks. It also includes a 64 x 32 -bit instruction cache. The instruction and data words are 32bit, while the addresses are 24 -bit. Both the multiplier and the ALU have 40 -bits floating-point operations and 32bits for integer operations. It has a 32-bit barrel shifter. Among the many advances in this processor, it can perform parallel multiply and ALU operations on integer or floating-point data in a single cycle. Another main feature of this processor is its internal dual-access memory capability.

In addition to the TMS320C30 DSP, this EVM has 16 K words of zero wait-state SRAM on the primary bus. It also has a voice quality analog data acquisition circuitry, with standard RCA jacks for line-level analog input and output. Beside an external serial port, it also has a 16-bit bidirectional PC host communication port. The unit is built on an IBM PC/AT compatible 8-bit half card that fits onto any PC compatible computer.

With this computing power, the EVM represents one of the latest technologies available in the market. It is, therefore, a suitable platform to test and to compare the various implementations for use in this study.

## CHAPTER 3

## 3. Background Information

### 3.1 Fourier Series and Fourier Transform

### 3.1.1 Fourier Series

What Fourier discovered in his experiments on heat flow is that a periodic function is expressible as the sum of an infinite number of sinusoids with a period that is the multiple of the fundamental frequency. The equation below is the mathematical realization of this discovery.

$$
x(t)=\frac{a_{0}}{2}+\sum_{n=1}^{\infty}\left[a_{n} \cos \frac{2 \pi n t}{P}+b_{n} \sin \frac{2 \pi n t}{P}\right]
$$

Here, $x(t)$ is a periodic time function that is integrable over its period $P$. The $a^{\prime}$ s and $b^{\prime}$ s are the Fourier coefficients, while $2 \pi / P$ is the fundamental frequency of the $x(t)$. The integral multiples of the fundamental frequency are the harmonic frequencies of $x(t)$.

Mathematically, Dirichlet's conditions ensure a convergent Fourier series. These conditions, as noted in [3], are

1. $x(t)$ is single-valued;
2. $x(t)$ has a finite number of discontinuities in the periodic interval;
3. $x(t)$ has a finite number of maxima and minima in the periodic interval; and
4.The integral $\int_{t_{0}}^{t_{0}+P}|x(t)| d t$ exists.

These are all sufficient conditions and not necessary conditions. Therefore, Fourier series can express any periodic functions meeting these requirements. However, periodic functions not meeting these conditions may still be expressible in Fourier series.

Fourier series leads to the definition of Fourier transform. Note the frequency-domain attributes in Fourier series in the next section, which discusses the development of Fourier transform.

### 3.1.2 Fourier Transform

Strictly speaking, Fourier transform is not a new transform. J.W. Nilsson [3] wrote, "It is a special case of bilateral Laplace transform with the real part of the complex frequency set equal to zero." Nevertheless, understanding the evolution from Fourier series to Fourier transform gives tremendous insights to the physical significance of this transform.

By replacing the sine and cosine terms in the Fourier series equation

$$
x(t)=\frac{a_{0}}{2}+\sum_{n=1}^{\infty}\left[a_{n} \cos \frac{2 \pi n t}{P}+b_{n} \sin \frac{2 \pi n t}{P}\right]
$$

with the identities

$$
\cos \theta=\frac{1}{2}\left(e^{j \theta}+e^{-j \theta}\right)
$$

$$
\sin \theta=\frac{1}{2 j}\left(e^{j \theta}-e^{-j \theta}\right), \text { and collecting like terms, the Fourier }
$$

series equation becomes

$$
x(t)=\sum_{n=-\infty}^{\infty} \frac{1}{2}\left[a_{|n|}-j \operatorname{sign}(n) b_{|n|}\right] e^{2 \pi n t / P}
$$

where $\operatorname{sign}(n)=\left\{\frac{1, n \geq 0}{-1, n<0}\right.$
Then let

$$
X(n)=\frac{1}{2}\left[a_{|n|}-j \operatorname{sign}(n) b_{|n|}\right]
$$

such that the equation becomes

$$
x(t)=\sum_{n=-\infty}^{\infty} X(n) e^{2 \pi n t / P}
$$

Therefore, $|X(n)|$ is the frequency magnitude at $2 \pi n t / P$,
where $1 / P$ is the fundamental frequency of the original
function. Note that the exponential functions are orthogonal as in

$$
\frac{1}{P} \int_{-P / 2}^{P / 2} e^{-j 2 \pi t / P} e^{-j 2 \pi t / P} d t=\delta_{k l}
$$

where $\delta_{k l}$ is the Kronecker delta function given by

$$
\delta_{k l}=\left\{\frac{1, k=l}{0, \text { otherwise }}\right.
$$

The summation index in the above equation can be changed to $l$. Then multiplying both sides of the equation by $e^{-j 2 \pi t / P}$, integrating from $-P / 2$ to $P / 2$, and applying the orthogonality equality gives the following equation.

$$
X(k)=\frac{1}{P} \int_{-P / 2}^{P / 2} x(t) e^{-i 2 \pi t / P} d t
$$

Following this, by multiplying each side with $P$, and taking limit on $P$, we get the following

$$
X(f)=\int_{-\infty}^{\infty} x(t) e^{-2 \pi t} d t
$$

This is the Fourier transform of $x(t)$. The inverse Fourier transform is therefore defined as

$$
x(t)=\int_{-\infty}^{\infty} X(f) e^{j 2 \pi f t} d f
$$

It becomes clear that the Fourier transform of a time function represents its frequency domain counterpart, as $X(n)$ determines the frequency magnitude. The roles of the exponential terms clearly relate the Fourier transform to the frequency domain.

As explained in the previous chapter, the Fourier transform exhibits CCP. This means that the product of the transforms of two time functions is equal to the transform of their convolution. This property has no apparent
usefulness unless a more efficient computation of the Fourier transform becomes available, which is very crucial to the study of signal processing as noted in the later sections. One other invaluable contribution of Fourier transform is the transformation of a time function to the frequency counterpart of the function. This essentially allows the ability to perform frequency analysis of any time function, an essential operation in most signal processing studies.

With the development in microelectronics technology, today's computing power increases many fold compared to that of only three decades ago. Combining these advances, and the many advantages of digital filter characteristics, it is undeniably practicable to conceive a digital form of the Fourier transform. Thus, the conception of DFT is a natural progression.
3.2 Signal Filtering and Convolution

The process of filtering signals involves modification of the frequency attributes of the signal. In most cases, such processes include removal or intensification of a certain range of frequency components of the signal. These processes can best be described as the multiplication of a filter sequence with the signal in the frequency-domain.

Assume $x(t)$ is the sampled signal and $h(t)$ is the filter. The transform of $x(t), X(f)$, and the transform of $h(t), H(f)$, are in the frequency-domain. Clearly, a term-wise multiplication of $H(f)$ to $X(f)$ modifies the frequency attributes of the signal $x(t)$. The results can then be reverse transformed to time-domain to produce the desired signal modification. This process is called convolution.

### 3.3 Discrete Fourier Transform

DFT is an adaptation of Fourier transform in situations where discrete quantization of a continuous function is necessary. This adaptation is most useful in digital signal processing where discrete numbers are processed. Without going into the details of the derivation, the following equation represents the DFT

$$
X(k)=\frac{1}{N} \sum_{n=0}^{N-1} x(n) e^{-j 2 . m n k / N}, k=0,1,2, \ldots, N-1
$$

The inverse discrete Fourier transform (IDFT) is also a summation, similar to DFT. This is shown as

$$
X(n)=\sum_{n=0}^{N-1} X(k) e^{j 2 m k / N}, k=0,1,2, \ldots, N-1
$$

### 3.3.1 Cooley-Tukey Algorithm

Starting with the DFT equation, as shown below, Cooley and Tukey employed a divide and conquer strategy to simplify the computation of the transform.

$$
X(k)=\frac{1}{N} \sum_{n=0}^{N-1} x(n) W^{n k}, W=e^{-j 2 \pi / N}
$$

They first divide the transform length $N$ into smaller length, as in $N=N_{1} \bullet N_{2}$. Letting

$$
\begin{aligned}
& n=n_{2} N_{1}+n_{1}, n_{1}=0,1,2, \ldots, N_{1}-1, n_{2}=0,1,2, \ldots, N_{2}-1 \\
& k=k n_{1} N_{2}+k_{2}, k_{1}=0,1,2, \ldots, N_{1}-1, k_{2}=0,1,2, \ldots, N_{2}-1
\end{aligned}
$$

Cooley and Tukey defined their FFT algorithm as follows.

$$
\begin{aligned}
& y_{n_{1}, k_{2}}=\sum_{n_{2}=0}^{N_{2}-1} x_{n_{2} N_{1}+n_{1}} W_{N_{2}}^{n_{2} k_{2}} \\
& y_{n_{1}, k_{2}}^{\prime}=y_{n_{1}, k_{2}} W_{N}^{n_{1}, k_{2}} \\
& X_{k_{1} N_{2}+k_{2}}=\sum_{n_{1}=0}^{N_{1}-1} y_{n_{1}, k_{2}}^{\prime} W_{N_{1}}^{n_{1} k_{1}}
\end{aligned}
$$

This modification breaks up the computation of DFT into two smaller pieces, $y_{n_{1}, k_{2}}$ and $x_{k_{1} N_{2}+k_{2}}$. Each of the smaller pieces can then be further broken up into even smaller pieces. In this way, the computational time complexity reduces from $O\left(N^{2}\right)$ to $O(N \log N)$

### 3.3.2 Radix-2 Fast Fourier Transform

The radix-2 FFT is a special case of the Cooley-Tukey FFT. This type of FFT has transform length $N=2^{n}$. Assuming that $N$ is the product of $N_{1}$ and $N_{2}$, where $N_{1}=2$, and $N_{2}=N / 2$, we get the following:

$$
\begin{aligned}
& X_{k_{2}}=\sum_{n_{2}=0}^{N / 2-1} x_{2 n_{2}} W_{N / 2}^{n_{2} k_{2}}+W_{N}^{k_{2}} \sum_{n_{2}=0}^{N / 2-1} x_{2 n_{2}+1} W_{N / 2}^{n_{2} k_{2}} \\
& X_{N / 2+k_{2}}=\sum_{n_{2}=0}^{N / 2-1} x_{2 n_{2}} W_{N / 2}^{n_{2} k_{2}}-W_{N}^{k_{2}} \sum_{n_{2}=0}^{N / 2-1} x_{2 n_{2}+1} W_{N / 2}^{n_{2} k_{2}}
\end{aligned}
$$

This form of radix-2 FFT is termed as decimation-intime (DIT). However, owing to the transform structure, it is necessary to rearrange the order of the input sequence. This process is called bit-reverse procedure. Essentially, the order of the input sequence is arranged such that the index has its bits reversed. For example, an $N=4$ transform sequence will have an input sequence of $0,2,1,3$ $(00,10,01,11)$.

By emphasizing the duality principle, taking $N_{1}=N / 2$ and $N_{2}=2$, we get the decimation-in-frequency (DIF) radix-2 FFT algorithm.

$$
\begin{aligned}
& X_{2 k_{1}}=\sum_{n_{1}=0}^{N / 2-1} W_{N / 2}^{n_{1} k_{1}}\left(x_{n_{1}}+x_{N / 2+n_{1}}\right) \\
& X_{2 k_{1}+1}=\sum_{n_{1}=0}^{N / 2-1} W_{N / 2}^{n_{1} k_{1}} W_{N}^{n_{1}}\left(x_{n_{1}}-x_{N / 2+n_{1}}\right)
\end{aligned}
$$

Somewhat different from the DIT algorithm, the output of this algorithm is in bit-reversed order when the input is in ascending order.

### 3.4 Number Theoretic Transform

When Pollard published his paper in 1971 [18], he had in mind analogous transforms to Fourier transform that also exhibit the CCP. Yet, these transforms are defined in finite field. As transforms defined in the rings of integers appeared since Argarwal and Burrus published their important paper in 1974 [19], the motivation had been an attempt to do away with the inaccuracy of complex operations due to limited word length. One other motivation had been the complete removal of multiplications that such transforms promised. Today, these motivations are still as credible. Such transforms in the rings of integers are now termed as number theoretic transform. Among the more popular NTT is FNT.
3.4.1 Fermat Number Transform

FNT is defined over the rings of integers modulo a Fermat number, $F_{t}$, defined as $2^{b}+1$, where $b=2^{t}$. This
transform and its inverse transform are defined as follows. The FNT is defined as

$$
\begin{gathered}
X_{k}=\left\langle\sum_{n=0}^{N-1} x_{n} \alpha^{\left\langle n k_{b}\right.}\right\rangle_{F_{t}}, \text { where } \quad k=0,1,2, \ldots, N-1 \\
\alpha^{N}=\langle 1\rangle_{F_{t}}, \text { and } \quad N=2^{m}
\end{gathered}
$$

while the inverse Fermat number transform (IFNT) is defined as

$$
\begin{aligned}
& x_{n}=\left\langle q \sum_{k=0}^{N-1} X_{k} \alpha^{\langle-n k\rangle_{b}}\right\rangle_{F_{t}} \\
& q=2^{-m}=\left\langle-2^{b-m}\right\rangle_{F_{t}}
\end{aligned}
$$

$\alpha$ is an integer of order $N$, transform length. If $\alpha$ is taken as the number 3 , it will have an order $N=2^{b}$. However, if $\alpha$ is taken as 2, it has an order of $N=2 b$. In this case, the transform is also called the Rader transform (RT). The transform is most efficiently implemented in this case, since most digital devices are designed to function in base 2.

When Argarwal and Burrus proposed Fermat number transform, they also suggested a set of arithmetic operations to make this transform possible. However, multiplication by powers of 2 is not as simple. Later, L.M. Leibowitze introduced a simplified binary number system named diminished-one number system to simplify arithmetic operations in the rings of integers modulo a Fermat number. The next section describes this number system.

### 3.4.2 Diminished-One Number System

Leibowitz defined a number $A$ to be represented by $\left[a_{b}, \ldots, a_{1}, a_{0}\right]$ where $0 \leq A \leq 2^{b}$. In this representation, the number zero is represented by $a_{b}=1$, and $a_{i}=0$ for $i=0,1,2, \ldots, b-1$. All other numbers are represented by the normal binary representation of $(A-1)$.

To add two numbers in this system involves taking the sum of the two numbers and adding the complement of the carry to the sum. However, if any of the numbers to be added is zero, the sum is set to the other number.

Negation in this number system is much simpler. Remembering that all operation in this number system is to modulo a Fermat number, negation of a number is simply the binary complement of the number. The only exception in this operation is, again, the number zero. In this case, the operation is inhibited.

Subtraction in this number system is defined as a combination of the above two operations. It involves a negation of the subtrahend and an addition to the minuend.

One of the more frequently used operations in Fermat number transforms is scaling. Scaling involves the multiplication with the roots of unity. In this case, the root is always a number that is a power of 2 . Thus, multiplication by powers of 2 becomes an important operation
in ensuring an efficient algorithm. Fortunately, this operation involves only left bit shifts and an addition of the complement of the carry bit. In other word, "for each factor of 2 , a left-circular shift of the $b-l s b$ 's is required and the bit circulated into the lsb is complemented."

The last operation that Leibowitz proposed was general multiplication. Here, he offered 3 methods. The first method involves multiplication of the two diminished-one numbers. This result is then added to the $b$-lsb of the diminished-one sum of the two numbers. Then one must perform a residue reduction of the result by a diminishedone subtraction of the $b$-msb's from the $b$-lsb's. The same rule regarding the number zero applies.

The second method requires translation to normal binary coding. The two numbers are then multiplied and a residue reduction as described above is applied. The result is the desired product.

The third method requires a translation of one of the numbers to normal binary coding and then doing a general diminished-one addition.

## CHAPTER 4

## 4. Implementation

### 4.1 Radix-2 Fast Fourier Transform Algorithm

### 4.1.1 Decimation-In-Time Algorithm

As presented earlier, the DIT FFT equation is as follows:

$$
\begin{aligned}
& X_{k_{2}}=\sum_{n_{2}=0}^{N / 2-1} x_{2 n_{2}} W_{N / 2}^{n_{2} k_{2}}+W_{N}^{k_{2}} \sum_{n_{2}=0}^{N / 2-1} x_{2 n_{2}+1} W_{N / 2}^{n_{2} k_{2}} \\
& X_{N / 2+k_{2}}=\sum_{n_{2}=0}^{N / 2-1} x_{2 n_{2}} W_{N / 2}^{n_{2} k_{2}}-W_{N}^{k_{2}} \sum_{n_{2}=0}^{k_{2}-1} x_{2 n_{2}+1} W_{N / 2}^{n_{2} k_{2}}
\end{aligned}
$$

This form of the Cooley-Tukey FFT divides a transform sequence into two smaller sequences, containing either the set of odd, or the set of even sequences. This corresponds to the first and second term of the above equations. Recursive application of the equation leads to further division of the two sequences into smaller sequences. This continues until each set has only one element remaining. Essentially, this requires recursive application to the first and second term in the equation.

Taking a cue from this, the algorithm for DIT FFT begins by pairing two elements at a time. This produces $N / 2$ two element pairs. To perform this operation, called
the butterfly operation, multiply a root of unity to the second element, add and subtract from the first, and then store the results. The result produces $N / 2$ terms. Combining two terms at a time, and repeating the same processes, results in $N / 4$ terms. Continue this until only one term remains. The following figure illustrates this process using a length eight transform sequence.


Figure 4. 1: DIT FFT algorithm (Extracted from [10])

As such, the construct of the following algorithm shows the iterative process. Each iteration corresponds to one layer in the above figure, that is a recursive application of the equation on itself. Within each iteration, perform butterfly operations on each element of the separate sets in
the sequence. This is how we get the two loops as shown in the algorithm below.

$$
\begin{aligned}
& n=\text { length } \\
& \text { for } l=1, \log _{2} n\{ \\
& m=2^{\prime} \\
& W_{m}=\text { root of unity } \\
& W=1 \\
& \text { for } j=0, m / 2-1\{ \\
& \text { for } k=j, n-1, m \text { \{ } \\
& t=W x(k+m / 2) \\
& u=x(k) \\
& x(k)=u+t \\
& x(k+m / 2)=u-t\} \\
& \left.W=W W_{m}\right\} \\
& \text { \} } \\
& \text { return } \mathrm{X}
\end{aligned}
$$

Figure 4. 2: DIT FFT pseudo code

Since this algorithm works best with bit reversed input, it makes sense to implement it on IFFT and allow the DIF algorithm to take care of FFT. In this way, there is less wastage in resources to modify input sequence and gives a more efficient implementation.

### 4.1.2 Decimation-In-Frequency Algorithm

The DIF algorithm is similar to that of the DIT except for the emphasis on duality. Instead of separating the transform sequence into sets of odd and even sequences, the algorithm pairs up elements of the set.

$$
\begin{aligned}
& X_{2 k_{1}}=\sum_{n_{1}=0}^{N / 2-1} W_{N / 2}^{n_{1}, k_{1}}\left(x_{n_{1}}+x_{N / 2+n_{1}}\right) \\
& X_{2 k_{1}+1}=\sum_{n_{1}=0}^{N / 2-1} W_{N / 2}^{n_{1}, k_{1}} W_{N}^{n_{1}}\left(x_{n_{1}}-x_{N / 2+n_{1}}\right)
\end{aligned}
$$

The above equations show the pairing of elements half the sequence length apart. Repeated application of the equation to itself leads to the efficient DIF FFT algorithm. The figure below depicts this process.


Figure 4. 3: DIF FFT algorithm (Extracted from [10])

Again, taking cue from the figure, the following algorithm begins by performing butterfly operations that are half the sequence length apart. The butterfly operation in this case consists of addition and subtraction of the two elements, followed by the multiplication of the root of unity to the difference of the two elements. This same process continues as the algorithm proceeds to the next layer.

$$
\begin{aligned}
& n=\text { length } \\
& \text { for } l=1, \log _{2} n\{ \\
& m=n / 2^{l-1} \\
& W_{m}=\text { root of unity } \\
& W=1 \\
& \text { for } j=0, m / 2-1\{ \\
& \text { for } k=j, n-1, m\{ \\
& u=x(k)-x(k+m / 2) \\
& x(k)=x(k)+x(k+m / 2) \\
& x(k+m / 2)=u W\} \\
& \left.W=W W_{m}\right\} \\
& \text { \} } \\
& \text { return } \mathrm{X}
\end{aligned}
$$

Figure 4. 4: DIF FFT pseudo code

Note that this algorithm will produce a bit reversed output sequence. It is, therefore, more suitable to implement the FFT. When performing a convolution, this bit reversed output sequence is fed into IFFT implemented in DIT algorithm. Such is a perfect combination that takes advantage of the characteristic of both DIT and DIF FFT algorithms.

### 4.2 Modified Diminished-One Operations

The idea behind the diminished-one number system is useful because it simplifies arithmetic operations when implementing FNT. This system eradicates the need to perform multiplication. Although not true in most modern digital signal processing processors like the one in use with this research, multiplication is usually the most expensive operation in most processors. All operations in this system consist of simple additions and bit shift operations. However, one of the disadvantages of diminished-one number system is the need to convert from an ordinary binary number before any such operations are useful. Moreover, scaling operations or multiplication by powers of 2 requires multiple steps to produce the desired result for higher powers of scaling factor. It defeats the purpose of employing FNT when this most frequently used
operation in a transform demands expensive processing resources.

The modified diminished-one algorithm employs the best of both worlds, normal binary and diminished-one arithmetic operations. Although the theoretical foundation is based on the diminished-one number system, this method attempts to solve the shortcomings of the diminished-one number system by turning back to ordinary binary operations whenever it is most convenient. Scaling has become a multiple bit rotation operation instead of a series of single bit rotations. These are explained in the following sections.

### 4.2.1 Negation

Negation of a number remains the same as in the diminished-one number system operation. Performing a binary complement on all the bits of a diminished-one number produces its negative counterpart.

### 4.2.2 Addition

This modification to diminished-one addition eliminates the need to check for the number zero. Therefore reducing the number of branching operations, which is the most expensive operation for the digital signal processor used in
this research. The operation assumes all numbers are in the rings of integers modulo a Fermat number, $F_{t}$. Therefore, the algorithm disregards all cases of adding negative numbers. An addition begins with normal binary addition and a condition check to determine if the number is indeed greater than or equal to the modulo. When the result is indeed greater than, or equal to the modulo, a conversion to the diminished-one number system enables easy modulo $F_{t}$ operation. The following equation shows that the sum of two numbers is one more than the value of the sum in the diminished-one number system.

$$
A+B=[(A+B)-1]+1
$$

With this insight, and taking that the range of any addition is no larger than twice the modulo, adding one to the diminished-one number is equivalent to adding the complement of the msb to the $b l s b^{\prime}$ s of the number. Since the maximum number of bits is $b+1$, and that the msb is $2^{b}$, the above conclusion is true as $\left\langle 2^{b}\right\rangle_{F_{t}}=-1$.

$$
\begin{aligned}
& k=l+m \\
& \text { if }\left(k \geq 2^{b}\right)\{ \\
& \quad k=k-1
\end{aligned}
$$

(subtract 1 to get diminished-one representation) complement msb and add to b lsb's (perform conversion from diminished-one to binary) \}
return $k$
Figure 4. 5: Modified diminished-one addition
Therefore, the algorithm for this operation is shown above in Figure 4.5 .

Notice the saving of one conditional check compared to the original diminished-one algorithm. This algorithm also has the advantage of not needing to convert a number into diminished-one number system in order to obtain the desired result.

### 4.2.3 Subtraction

The subtraction algorithm is similar to the addition algorithm. The rationale is the same, except that this algorithm is much simpler to implement. Like the addition algorithm, the following equation shows the connection
between normal binary representation and the diminished-one representation of the difference of two numbers.

$$
A-B=[(A-B)-1]+1
$$

This algorithm assumes that all inputs are in the ring of integers modulo $F_{t}$, as in the addition operation. Thus the largest difference is $F_{t}-1$ and the smallest difference is $-\left(F_{t}-1\right)$. When the difference is a positive number, the algorithm does nothing more. When the difference is a negative number, the algorithm retains only the $b l s b^{\prime} s$ of the number.

Employing the same rationale as the addition algorithm, theoretically this algorithm converts the difference to diminished-one representation when it is negative. This eliminates the conditional checks for the number zero and thus the inevitable branch operations. When using the diminished-one representation, a residue reduction on the number accomplishes the modulo $F_{t}$ operation. Residue reduction involves the addition of the complement of the $b$ $\mathrm{msb}^{\prime} \mathrm{s}$ to the $b$ lsb's.

Since a negative number has all $b$ msb's equal to 1 , its complement is always zero. For all possible negative numbers except the smallest, this involves subtracting one from the $b$ lsb's and adding zero. Following this is a code conversion to normal binary number, which is the addition of
the complement of the $b+1$ th bit to the $b$ lsb's. For this case, it is the addition of the number one. This algorithm removes the redundancy of subtracting and later adding one to the $b$ lsb's by simply retaining the $b$ lsb's of a negative number. For the smallest possible negative number, such as the binary number with $b$ ones followed by $b$ zeros, it is different. After converting to diminished-one representation and performing residue reduction, all bits except the $b+1$ th bit are one. A code conversion to normal binary representation gives the same results as in retaining the $b$ lsb's. Therefore, the algorithm is as shown below.

$$
\begin{aligned}
& k=l-m \\
& \text { if }(k<0)
\end{aligned}
$$

$$
k=\mathrm{b} l \mathrm{sb}^{\prime} \mathrm{s} \text { of } k
$$

return $k$
Figure 4. 6: Modified diminished-one subtraction

As in the addition operation, this algorithm also removes the need for number system conversions and the need to check for the number zero.

### 4.2.4 Scaling

The scaling operation is essentially an extension to the diminished-one scaling operation. Noted in the previous chapter, scaling in the diminished-one number system involves rotating the complement of the msb to the lsb. This is easily seen in the following equality.

$$
(2 A-1)=2(A-1)+1
$$

However, this operation is a single bit operation. Therefore, a multiplication of higher powers of 2 requires several scaling operations to accomplish. The proposed algorithm extends the diminished-one scaling operations to multiple bit operation. Noting that the maximum power of 2 in the multiplication of the scaling factor is $2 b$, or the maximum transform length for FNT . This operation needs only be concerned with a maximum of $2 b$ bit rotations. Subsequent paragraphs will explain the operation using a combination of bit shift, 'xor', and 'or' logic operations. This is so because rotation is not a native operation of the digital signal processor used in this research,.

Referring to the following figures, the left figures represent a number while the right figures represent the same number, d2, with bit extension, d1. A single bit rotation in the left figures is equivalent to a left bit shift and an addition of the complement of the bit shifted
into the dl field. Thus a multiple bit rotation in the left figures is then the same operation as multiple bit shift and addition of the complement of the bits shifted into di to d2. The scaling algorithm takes advantage of the above idea to simplify the diminished-one scaling operation.

Assuming scaling by $2^{x}$, and that mask $=2^{b}-$, the following figures show the inner working of this algorithm.


Figure 4. 7: Diminished-one number A


Figure 4. 8: Diminished-one number $A$ after less than bits rotation


Figure 4. 9: Diminished-one number $A$ after more than b bits rotation

In the above figures on the left, the shaded areas are the complemented bits rotated. The shaded areas in the right figures represent the original bit sequence. When a rotation is less than $b$ bits, figure 2 shows that the msb's
of a number is rotated into the di zone. However, when the bit rotation is more than $b$ bits, the lsb's of the number gets into the di zone. Whenever the bits are in zone di, take their complement, and 'or' them to the bits in zone d2 to give you the diminished-one result of the scaling operation.

```
convert \(A\) to diminished-one representation
\(\mathrm{d} 1=\mathrm{d} 2\) left shift \(x-b\) bits
mask \(=\) mask left shift \(x-b\) bits
d1 = d1 xor mask
if (bit shift <b)
    \(\mathrm{d} 2=\mathrm{d} 2 \ll x\)
    else
    \(\mathrm{d} 2=\mathrm{d} 2 \ll x-2 b\)
\(\mathrm{d} 2=\mathrm{d} 1\) or d 2
    convert d2 to normal binary representation
    Figure 4. 10: Diminished-one scaling
```

Therefore, the above algorithm first converts a number into its diminished-one representation. A left shift of $x-b$ bits gives the bits shifted into zone dl. Perform the same number of bit shifts to the mask and then do a 'xor' with it to produce the complements of the bits shifted into zone d1. The result is stored in a register conveniently named di. In the case when the number of bit rotation is more than $b$, the msb's will have been complemented twice.

Therefore, this method does not perform these complements and simply left shifts the original number by $x-2 b$. Take note that a negative left shift implies a right shift. The result is then stored in register d2. This is then 'or' with the value in di to produce the desired result.

### 4.2.5 Multiplication

Multiplication remains the same as method 2 proposed by Leibowitz. A normal binary multiplication result in a product, which is the desired product in diminished-one representation. This is followed by a residue reduction. The last step in this algorithm is a code conversion of the product to obtain the normal binary product. Figure 4.6 shows the process of this operation.

Since the algorithm is essentially the same as Leibowitz's diminished-one algorithm, the author will not discuss the algorithm any further. However, as this implementation involves 33 bit operation, note that this implementation assumes three 16 bit parts in a number. This is because the multiplication operation in the digital signal processor used involves 16 bits numbers and produces a product with 24 bits. By separating a number into three 16 bit parts, multiplication becomes a multiple process.


The figure above shows the process of multiplying two numbers. Each part of a number is multiplied to the components of the other number. The results are combined to produce the actual product. A residue reduction follows, giving the diminished-one product. This number then goes through a code conversion to obtain the binary representation of the desired result.

## CHAPTER 5

## 5. Data Analysis

As described in the preceding chapter, the filter implementations use both NTT and DFT. Both implementations use the Texas Instruments' TMS320C3X digital signal processor. The three filters are lowpass, bandpass, and highpass filters. Applying these signals to a filter, as presented in the subsequent section, modifies the signal accordingly. The following sections will look at these data and compare them, in the frequency domain, with the original signal. This serves to verify the validity of the algorithm. Analysis of execution time and memory requirements of each implementation will then follow.

### 5.1 General Data Output

The following sub-sections will look at an input sample and the filtered samples, both in time-domain and in frequency-domain. The input signal obtained via the input port of the TMS320C3X evaluation module has a transform length of 64 words. Performing convolution with the three filter sequences produces the filtered outputs. These output sequences are then compared with the original input data.

### 5.1.1 Sample Data

The following diagram shows the input data in its timedomain representation. Performing a Fourier transform on this data sequence produces the frequency-domain sequence of the input data, as shown in the next figure. Both figures show the real and the imaginary portion of the signal.


Figure 5. 1: Input data sequence


Figure 5. 2: Input data sequence in frequency-domain

Note that the frequency-domain data sequence shows a significant amount of lower frequency components. Also note the symmetry in the figure. Referring to the definition of the Fourier transform in chapter 2 , one can find the term $|n|$, and that the summation spans from negative $n$ to positive $n$. This accounts for the symmetry seen here. Thus, the center of this figure represents the highest frequency components.

### 5.1.2 Lowpass Filtering

Having looked at the original input sequence, the following figure presents the lowpass filtered sequence.


Figure 5. 3: Lowpass filtered sequence using DFT

Figure 5.3 shows the filtered sequence using DFT and Figure 5.4 shows the filtered sequence using NTT. Notice the similarity of the two figures.


Figure 5. 4: Lowpass filtered sequence using NTT

The values of the output from the NTT version are significantly higher. However, this is due to the fact that the lowpass filter for the DFT method is scaled to unity, while that for the NTT remains in its original form.


Figure 5. 5: Lowpass filter sequence in frequency-domain

The above figure shows the lowpass filter in frequencydomain. This filter has significantly larger low frequency components and tapers towards the higher frequency. Therefore, the filtered result of the input sequence is expected to contain a fair amount of lower frequency components, while the higher frequency components diminish after filtering.

Looking at the filtered sequence below, the results are just as expected. The higher frequency components of the input sequence are diminished, while the lower frequency region remained.


Figure 5. 6: Lowpass filtered output sequence in frequency-domain

### 5.1.3 Bandpass Filtering

The following two figures show the bandpass filtered output using DFT and NTT convolution respectively. Again,
the output sequences have exactly the same shape, with varying amplitudes. The range of the data value is, again, different since the DFT bandpass filter is scaled to unity.


Figure 5. 7: Bandpass filtered sequence using DFT


Figure 5. 8: Bandpass filtered sequence using NTT

After observing the similarity between the above two outputs, the following two figures present the frequency-
domain output for analysis. The bandpass filter shows a large amount of mid-range frequency components and a fair amount of these components consist of lower frequencies. This being so, the filtered output should show a significant decrease in high frequency components, while retaining most of the mid-range and some of the lower frequency components, which is demonstrated in figure 5.10.


Figure 5. 9: Bandpass filter sequence in frequency-domain


Figure 5. 10: Bandpass filtered output sequence in frequency-domain

As in the above figures, the following figures show the highpass filtered output from both DFT and NTT convolution methods. Again, note that the NTT convolution methods do not produce the imaginary portion. However, although the ranges of the data values are different for the same reason as above, the shape of these sequences are the same.


Figure 5. 11: Highpass filtered sequence using DFT


Figure 5. 12: Highpass filtered sequence using NTT

The following figure shows the highpass filter in the frequency-domain. This particular highpass filter consists of some low frequency components and has a large portion of its components in the higher frequencies. Therefore, the filtered output is expected to contain mostly high frequency components and the mid-range frequencies will be absent or filtered off. This is shown in figure 5.14, which is the filtered output in the frequency-domain.


Figure 5. 13: Highpass filter sequence in frequency-domain


Figure 5. 14: Highpass filtered output sequence in frequency-domain

The results from the above data show that the filters perform as they are designed to do. The exact shape of both implementations shows consistency in the two implementations, therefore, laying the groundwork for comparison of both implementations.

### 5.2 Execution Time

The following table shows the number of clock cycle to execute each operation in both NTT and DFT implementations.

|  | NTT |  |  | DFT |
| :---: | :---: | :---: | :---: | :---: |
| Clock Cycle | Lowpass | Bandpass | Highpass | All cases |
| Filtering | 16302 | 16308 | 16298 | 6832 |
| Transformation | 8806 | 8806 | 8806 | 3560 |

The data indicates significantly lower number of clock cycles for DFT implementation. The conclusion is, therefore, favorable towards DFT implementation compared to NTT implementation in this environment.

A similar conclusion prevails when using the number of operation as a measure. Table 5.2 shows that the NTT implementation accounts for a significantly larger number of operations, which include addition, subtraction,
multiplication, 'and', 'or', 'xor', 'not', and shift operations.

|  | NTT |  |  | DFT |
| :---: | :---: | :---: | :---: | :---: |
| No. Operations | Lowpass | Bandpass | Highpass | All cases |
| Filtering | 15112 | 15085 | 15077 | 3852 |
| Transformation | 5159 | 5159 | 5159 | 1790 |

Table 5. 2 Number of operations

This finding differs from many research literatures on NTT. The difference is due to two reasons. Firstly, the DSP chip in this research environment performs real multiplications with 1 clock cycle, which are the same as real additions and subtractions. This is contrary to the general belief that multiplication is more expensive than other operations. Secondly, even though complex operations take a few real operations to complete, they are still better off compared to operations in modulo arithmetic. The reason is that existing DSPs do not perform modulo arithmetic. Therefore, for example, a simple modulo addition will consist of a number of integer additions, shifts, and 'xor' operations. Until there is efficient hardware implementation to modulo arithmetic in the market, NTT is not a better solution compared to DFT.

### 5.3 Memory Requirement

Memory requirement in the case of DFT requires a 32 -bit word for the real and the imaginary portion of a complex number. Therefore, it requires 2 memory locations for each data point. An additional array of $1.25 n$ words, where $n$ is the sequence length, is required for the DFT. This array stores the scaling factors, the $\omega^{\prime} s$, in order to increase computational speed to complete the DFT. While FNT requires 33 bit data point, it takes up 2 memory locations for each data point in practice. The msb of a data point will occupy one memory location, which is a waste of memory resources. However, future development may lead to more efficient use of memory. In view of this, the FNT uses less memory space compared to the DFT.

### 5.4 Summary

In summary, this chapter verifies the correctness of the implementations of DFT and FNT in this study. The time, or number of clock cycle taken in the FNT implementation is significantly higher than that of the DFT implementation. When counting the number of operations needed to perform the two operations, FNT shows the same disappointing results. The amount of memory requirement for the FNT, however, is lesser compared to the DFT.

## CHAPTER 6

## 6. Analysis and Conclusion

### 6.1 Analysis

### 6.1.1 Speed

Referring to table 5.1 and table 5.2 on the number of execution clock cycle and the number of operation respectively, this study consistently indicates the poorer execution time performance of the FNT. This is contrary to the general belief that the FNT takes shorter computational time.

Agawal and Burrus commented in their 1974 paper [19], "To compute the convolution using the FFT, most of the time is taken in computing the complex multiplications required to compute the transform." They also said that, "A comparison with the RT reveals that these complex multiplications are replaced by bit shifts and subtractions which are much faster operations." This assumption that complex multiplications have poorer time performance than bit shifts and subtractions was valid in the 1970's. It is rightly so, especially when their comparison was verified on the IBM 370/155. Nevertheless, technological advances over
the past twenty years have changed the validity of these statements. The results from this study strongly indicate the repercussion from this improved technology. There are two reasons the results from this study deviate from Agawal and Burrus's conclusion.

Firstly, multiplications are no longer expensive and time consuming operations. In the TMS 320 C 30 hardware environment where this study does most of its computation, multiplications take only one clock cycle. This is the same number of clock cycle as operations like additions, subtractions, bit shifts, etc. One complex multiplication, therefore, takes only six clock cycles; four multiplications, one addition, and one subtraction. Compare this to implementing diminished-one multiple-of-two operation in the TMS320C30 environment, which takes three shifts, one 'xor', and an addition. This will take five clock cycles. Multiplication is now comparable to bit shifts and subtractions in terms of time complexity.

Secondly, the traditional practice of considering only multiplications in time complexity analysis is not justifiable. This is because multiplications need to be of equal weighting with the other arithmetic operations in time complexity analysis, since they all take the same amount of time to execute. All types of operations need to be considered in the analysis. As such time complexity
analysis will also include additions, subtractions, bit shifts, etc. Since these operations are taken into consideration, and the FNT uses a lot of such operations, the time complexity of the implementation of the FNT becomes much higher compared to the DFT. The FNT clearly stands out to be more time consuming. This is verified in table 5.1 and table 5.2.

### 6.1.2 Memory Requirement

Memory requirement for the DFT is more than that of the FNT implementations. Since the DFT is in the complex field, it requires one word each for the real and the imaginary component. Therefore, a total of two words is needed for each element in the transform sequence. In addition to this memory requirement, the DFT implementation requires an array of scaling factors, the $\omega^{\prime} s$, to speed up execution time. This array occupies $2.5 n$, where $n$ is the sequence length, words. In this implementation, the word length of the FNT is 33 bits. Since a word occupies 32 bits in this case, each element in the transform sequence for the FNT requires 2 words. Future work may aim at improving space complexity of FNT. This is because most of the bits in the most significant word are not needed. Therefore, the
implementation of $F N T$ in this study requires less memory space as the DFT implementation.

### 6.1.3 Accuracy

The most attractive advantage of the FNT is the degree of accuracy it offers in computing convolution. There are two sources of error in digital signal processing. They are the quantization error and the computation roundoff error. When sampling a signal, the equipment used introduces limitations caused by the finite precision of the arithmetic units and the limited capacity of the memory. Since the sampling devices and the memory have limited word length, the sampled data in the memory represent approximations to the actual signal. These are the causes for quantization errors. Both the DFT and the FNT suffer from quantization errors. For all praćticality, it is unavoidable. The degree of approximation depends on the word length of the equipment used.

Among the limitations of the FNT is the requirement that all values of the final outcome for the transform must not exceed the modulo. This limitation requires scaling of the input data in order to prevent any overflow. Errors are introduced in this scaling process. However, there are no computational roundoff errors. This is because the
transforms are computed in rings of integers modulo a Fermat number. In computing the DFT, some processes of additions, subtractions, and multiplications increases the number of bits in representing the resulting complex numbers of these operations. However, the number of bits available remains unchanged within the machines. This makes it necessary to limit the wordlength throughout the calculations. As such, rounding off the results from the operations becomes necessary too. Roundoff errors occur at every operation that produces results exceeding the wordlength of the machine. Therefore, errors can be introduced at all stages of computing the transform. This lack of roundoff errors during computation for the FNT is an advantage over the DFT. The FNT has its advantages and disadvantages. When execution speed is crucial, the DFT is a better choice than the FNT. With the current hardware technology, implementing the FNT will increase the amount of time taken to perform the transform. However, when accuracy is important, the FNT offers highly accurate results compared to the DFT.

### 6.2 Conclusion

The field of signal processing has matured tremendously over a little less than two centuries, most especially during the last three decades. Coupled with the advances in microelectonic industry, the many advantages in digital
filtering techniques have spurred the study of digital signal processing.

Over this time, the paper published by Cooley and Tukey set an important landmark. Their method increased computational efficiency of calculating the Fourier transform many folds. Other researchers have also introduced improved algorithms to their method over the last few decades. However, in 1974, Rader introduced a new transform, generally referred to as the number theoretic transform, in the hope of eradicating the shortcomings of the Fourier transform. Number theoretic transform uses integer modulo arithmetic instead of complex arithmetic. Thus, it is possible to perform the transform without the use of multiplication, which is a traditionally expensive operation using the Fourier transform.

This study takes a look at the many claims of number theoretic transform, specifically FNT. Comparisons in execution time, number of operation, and memory requirement by both DFT and FNT using radix-2 FFT algorithm are done. All these methods are implemented on the Texas Instruments' TMS320C3X digital signal processing chip. This study also presents an analytical comparison of computational accuracy of the DFT and the FNT.

Results from this study show that the execution time, or the number of clock cycles (Table 5.1) for the FNT
implementation is considerably higher than that of the DFT implementation. In order to have a fair comparison, the study also look at the number of operation for both implementations. Again, FNT shows a discouraging higher value (Table 5.2). However, based on analytical analysis, the FNT requires lesser memory space when compared to the DFT. In terms of computational accuracy, the FNT also performs much better. The only error introduced in implementing FNT is during input quantization [21]. There are no computational roundoff errors in FNT. This is not the case for DFT.

This research also introduces modified diminished-one number operations. The results from this study show the feasibility of these operations. Future development in this area should include hardware implementation of these operations. An advantage of these operations over Leibortze's original diminished-one number system proposal is the lack of number system conversion for both addition and subtraction operations. Both these operations also remove the need to check for the number zero. Scaling or multiplication by powers of 2 operation becomes a one-step operation instead of multi-step operation.

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APPENDIX

## APPENDIX A

## Software User's Instruction

## System Requirements:

1. IBM PC or PC compatibles with Intel 80386 or above microprocessor.
2. Texas Instruments' TMS320C30 Evaluation Module (EVM).
3. DOS 5.0 or above.
4. Windows 3.1 or above.
5. Borland custom control tools library bwcc.dll

Starting The Software:

1. Ensure that TI's TMS 320 C 30 EVM is properly installed.
2. Ensure that the client program 'child.out', the EVM loader 'evmload.exe', and the three initialization files 'resvct.001', 'resvct.002', 'resvct.004' are in the same directory as 'host.exe'.
3. Run Windows 3.1
4. Select 'Run' from Program Manager's 'File' Menu
5. Type 'host.exe' and punch the Enter key.
6. 'host.exe' will load the TMS320C30 EVM client program, 'child.out', initiate and start the program running in the EVM.
7. 'host.exe' will then return to the windows environment.
8. If 'host.exe' couldn't locate the TMS320C30 EVM, or the client program 'child.out', it will inform the user and prompt for further action.

Moving Around The Software:


Figure 1: Host program's interface

1. Item 'Convert', under the 'File' Menu, allows user to convert filter files computed from Hypersignal to data files in the format for this program.
2. item 'About', under the 'Help' Menu, displays information about this program.
3. Button ' $F$ ' is the filter button. User must select filter, output, and input files before this function
will work. After the user points the mouse pointer at this button and click it once, the program will filter the input file using the filter file selected.
4. Button ' $T$ ' is the transform button. Selecting this function will start a transform operation on the input file using the type of transform selected. The selection of the type of transform is discussed below.
5. Button ' $R$ ' is the reset button. This function will reset the TMS320C30 EVM client program.
6. Button 'S' is the sample button. The EVM will sample input signal from the EVM input port. This 64-word data is then sent to the PC. The data is then saved using the output filename.
7. Button ' $N$ ' is the name button. When selected, the message box just below the buttons will display all the selected filenames.
8. When 'Filter File' button is selected, the user is prompted for a filter filename from a pop up window.
9. When the 'Output File' button is selected, the user is prompted for an output filename from a pop up window.
10. When the 'Input File' button is selected, the user is prompted for an input filename from a pop up window.
11. The 'Input' button, when selected, enables an input file to be used. Otherwise, the EVM will sample from
its input port and use the data collected as input data for any operation.
12. When the 'DFT(NTT)' button is highlighted, all operations are performed using DFT algorithm. Otherwise, all operations are performed using NTT algorithm.
13. When the 'TI(PC)' button is highlighted, all operations are performed using the TI's TMS320C30 EVM. Otherwise, all operations are performed using the PC.
14. Below all the buttons is the message box. This is the area where the program will display messages for the user.
15. To the right of the message box is the display list box. Pointing and clicking on the arrow will display a list of items. Selecting an item selected from the list box will display the item in the display area.
16. The display area is below the menu and toolbar. This is the area where data is displayed.

## APPENDIX B

## Program Source Code

| .width | 104 |
| :--- | :--- |
| .length | 2000 |
| .global | SINE, N, M |
| .global | iinverse, cinverse |
|  |  |
| .data |  |



* ADDRESSES OF CONSTANTS


| fftsize | .word | N |
| :--- | :--- | :--- |
| logsize | .word | M |
| sinetab | .word | SINE |
| IINVERSE | .word | iinverse |
| CINVERSE | .word | cinverse |



* CONSTANT VARIABLES


| mask | .word $0 f f f f h$ | ; mask for ffnt |
| :--- | :--- | :--- |
| mid_carry | .word | $010000 h$ |
| shiftmask | .word 0 ;arry over |  |
|  | fffffffh | ; mask for power of 2 multiplication |

.text
FP .set
AR 3
.ref
Com_saddrl


* GLOBAL DECLARATION OF FUCTIONS



| addi | ar2, ar $4, \operatorname{ar} 5$ | ; $\operatorname{ar5}$-> $\cos (2 *$ pi*j/m) |
| :---: | :---: | :---: |
| ldi | r1, rc | ;repeat $\mathrm{N} / \mathrm{m}$ times |
| subi | 1, rc |  |
| rptb | floop 2 nf |  |
| subf | *ar1,*ar0, r3 | ; $\mathrm{r} 3<-\mathrm{x}[\mathrm{k}]-\mathrm{x}[\mathrm{k}+\mathrm{m} / 2]$ |
| subf | * +ar1,*+ar0, r4 | ; $\mathrm{r} 4<-\mathrm{y}[\mathrm{k}]-\mathrm{y}[\mathrm{k}+\mathrm{m} / 2]$ |
| mpyf | r3,r5, ro | ; $r 0<-(x[k]-x[k+m / 2]) \sin (2 * p i * j / m)$ |
| \||adde | * +ar1,*+ar0, r2 | ; $22<-y[k]+y[k+m / 2]$ |
| mpyf | *ar5,r4,r1 | ; $\mathrm{r} 1<-(\mathrm{y}[\mathrm{k}]-\mathrm{y}[\mathrm{k}+\mathrm{m} / 2]) \cos (2 * \mathrm{pi} * \mathrm{j} / \mathrm{m})$ |
| \||stf | r2,*+ar0 | ; $Y[k]<-Y[k]+y[k+m / 2]$ |
| subf | ro, r1 | $; \mathrm{r} 1=\mathrm{b} \cos ()-\mathrm{a} \sin ()$ |
| mpyf | *ar5,r3, r0 | ; $\mathrm{r} 0<-(\mathrm{x}[\mathrm{k}]-\mathrm{x}[\mathrm{k}+\mathrm{m} / 2]) \cos (2 * \mathrm{pi} * \mathrm{j} / \mathrm{m})$ |
| \||stf | r1,*+ar1 | $; y[k+m / 2]<-b \cos ()-\mathrm{a} \sin ()$ |
| mpyf | r4,r5,r1 | ; $\mathrm{r} 1<-(y[k]-y[k+m / 2]) \sin (2 * p i * j / m)$ |
| \| |addf | *ar1,*ar0،r2 | ; $\mathrm{r} 2<-\mathrm{x}[\mathrm{k}]+\mathrm{x}[\mathrm{k}+\mathrm{m} / 2]$ |
| addf | r0, r1 | ; $\mathrm{r} 1=\mathrm{a} \cos ()+\mathrm{b} \sin ()$ |
| floop2nf: |  |  |
| ste | r2,*ar0++(ir0) | ; $\mathrm{x}[\mathrm{k}]=\mathrm{x}[\mathrm{k}]+\mathrm{x}[\mathrm{k}+\mathrm{m} / 2]$ |
| \||stf | r1,*ar1++(ir0) | $; x[k+m / 2]=a \cos ()+b \sin ()$ |
| br | floop 2 f |  |
| floopnf: |  |  |
| lsh | -1,ir0 | ; m |
| Ish | 1.ir1 | ; N/m |
| subi | 1.r6 | ; decrement main loop count |
| bp | flooplf |  |
| pop | FP |  |
| rets |  |  |



* Floating point scaling by $1 / \mathrm{N}$


* This routine multiply every elements in the input sequence by
* the inverse of the transform length. The address of the input *
* sequence is send to this function at location FP-2. The value of *
* inverse of the transform length is stored at the memory location *
* specified at CINVERSE
$\star$
_fscale:
push
ldi
FP
ldi
SP, FP
sti ar0,@_com_saddrl
ldi @CINVERSE,ar1 ;arl gets address of constant $1 / \mathrm{N}$
ldf *ar1,r0
ldi
@fftsize, rc
; ro<- $1 / \mathrm{N}$
mpyi 2,rc
subi $1, r c$
rptb fscaling ;begin loop
mpyf
fscaling: stf
*ar0, ro,r1
r1,*ar0++
; multiply by $1 / \mathrm{N}$
; store result
pop
FP
rets


| 1 di | @_com_saddrl, ar0 | ; aro->x[0] |
| :---: | :---: | :---: |
| addi | r6, ar0 | ; $\operatorname{ar0} 0$-> $x[k]$ |
| addi | ar3, ar0, arl | ;arl -> $x[k+m / 2]$ |
| $1 d i$ | irl, rc | ;repeat $\mathrm{N} / \mathrm{m}$ times |
| subi | 1, rc |  |
| rptb | floop 2 ni |  |
| mpyf | * +ar1, *ar5, r3 | ; $r 3<-y\left[k+m / 2{ }^{*} \cos (2 \star p i * k / m)\right.$ |
| mpyf | *ar1,*ar4,r0 | ; $\mathrm{r} 0<-\mathrm{x}[\mathrm{k}+\mathrm{m} / 2] * \sin (2 * \mathrm{pi*k} / \mathrm{m})$ |
| mpyf | *ar1,*ar5,r1 | ; $\mathrm{rl}<-\mathrm{x}[\mathrm{k}+\mathrm{m} / 2]^{*} \cos (2 \star \mathrm{pi} k \mathrm{k} / \mathrm{m})$ |
| \||addf | ro,r3,r2 | ir2 <- b $\cos ()+\mathrm{a} \sin ()$ |
| mpyf | * +ar1,r5,r0 | ; $\mathrm{r} 0<-\mathrm{y}[\mathrm{k}+\mathrm{m} / 2]^{*} \sin \left(2^{\star} \mathrm{pi} \mathrm{A}^{*} / \mathrm{m}\right)$ |
| \||addf | * +ar0, r2,r3 | ;r3<-y[k] + b $\cos ()+\mathrm{a} \sin ()$ |
| subf | ro,r1,ro | ; $\mathrm{r} 0<-\mathrm{a} \cos ()-\mathrm{b} \sin ()$ |
| subf | r2, **ar0, r1 | ; $\mathrm{r} 1<-\mathrm{y}[\mathrm{k}]-\mathrm{b} \cos ()-\mathrm{a} \sin ()$ |
| \||stf | r3,*+ar0 | $; y[k]<-y[k]+b \cos ()+a \sin ()$ |
| addf | *ar0,r0,r1 | ; $\mathrm{rl}<-\mathrm{x}[\mathrm{k}]+\mathrm{a} \cos ()-\mathrm{b} \sin ()$ |
| \||stf | r1,*+ar1 | i $y[k+m / 2]<-y[k]-b \cos ()-a \sin ()$ |
| subf | ro,*ar0,r1 | ; $\mathrm{r} 1<-\mathrm{x}[\mathrm{k}]-\mathrm{a} \cos ()+\mathrm{b} \sin ()$ |
| \||stf | r1,*ar0++(ir0) | ; $\mathrm{x}[\mathrm{k}]=\mathrm{x}[\mathrm{k}]+\mathrm{a} \cos ()-\mathrm{b} \sin ()$ |
| 2ni: |  |  |
| stf | r1,*ar1++(ir0) | $; x[k+m / 2]<-x[k]-a \cos ()+b \sin ()$ |
| br | floop2i |  |
| oni: |  |  |
| subi | 1, r7 | ; decrement main loop count |
| bnz | floop1i |  |
| pop | FP |  |
| rets |  |  |



* Complex multiplication

$\star$
* This routine performs a term-wise multiplication of the * transformed input sequence to the transformed filter sequence.
_fmult:
push
ldi
FP
SP, FP
*-FP(2), ar0
*-FP (3), ar1
*-FP(4), ar2
2,irl
ldi @fftsize,rc ;setup repeat loop number
subi
rptb
mpyf
mpyf
mpyf
||addf
mpyf
subf
stf
fmloop: stf
pop
FP
rets

addi and
nlooplnf:
index
nloop2f:
subi
bzd
ldi
ldi
addi
addi
ldi
subi
rptb
addi
addc
bzd
ldi
subi
subb
xor
addi
and
ndiff2f:subi


## subb

bnd
sti
||sti
mpyi
1sh
subi
subb
bnn
brd
ldi
nop
nop
r4,r3,r1
ar2,st,r2
; mod operation ; save carry
sti
||sti

```
r2,*+ar0
r1,*ar0++(ir0)
```

;save high word sum ; save low word sum, and increment

```
;decrement r7
```

;end routine if zero
; register ar2 <-1
; $\operatorname{ar0} 0$ - $x[0]$
;ar0 -> $x[k]$
;arl -> $x[k+m / 2]$
;repeat $\mathrm{N} / \mathrm{m}$ times
;r1 <- binary sum, low word
ir2 <- binary sum, high word
;if sum < 2^32, store result
; register ar3 <- 0
; convert to d-1, low word
; convert to $\mathrm{d}-1$, high word
$; A+B=[(A+B)-1]+1$. Thus $d-1$
; mod operation
; save carry
;r3 <- binary diff, low word
; $44<-$ binary diff, high word
;if diff is negtive, $r 3$ is in $d-1$
; save high word
; save low word, and increment index
; \# of bit shift
; adjust bit shift for double
; counting
; convert to d-1 low word
; convert to d-1 high word
;if not zero, scale
;if equal zero, make r4 $=0$
; X - N/2 shift, shift d2

| bnd | nscalef | ;if shift less than $N / 2$, next shift ;X |
| :---: | :---: | :---: |
| 1sh | r2,ar7,r6 | ; shift mask by X - N/2 |
| 1 sh | r2,r3,r5 | ; shift d-1 data by X - N/2 |
| xor | r5, r6 | ; complement r5 |
| subi | @fftsize,r1 | ; shift more than $N / 2$, adjust next ; shift |
| nscalef: |  | ; X - N |
| 1sh | r1, r3 | ; left shift X or X-N bits |
| or | r6,r3 | ; or register to get final d-1 result |
| ndonef: addi | 1, r3 | ; convert to binary low |
| and | ar2,st,r4 | ; convert to binary high |
| nloop2nf: |  |  |
| sti | r3,*ar1++(ir0) | ;store results |
| \||sti | r4,**ar 1 |  |
| br | nloop2f |  |
| nloopnf: |  |  |
| 1sh | -1,ir0 | ;update ir0, m/2 |
| 1 sh | 1,ir1 | ; update irl, $\mathrm{N} / \mathrm{m}$ |
| subi | 1, ro | ; update r0, decrement |
| bnz | nloopf |  |
| pop | FP |  |
| rets |  |  |



```
* Diminished-one scaling by inverse of transform length N
```



```
*
* This routine multiplies all terms in the input sequence by a *
* scaling factor specified in the memory location IINVERSE. *
* Since \(2^{\wedge} b\) is always the multiplicative inverse of itself *
* modulo \(2^{\wedge} b+1\), multiplicative inverse of all other numbers *
* require only b bits. The ( \(b+1\) )th bit of the multiplicative *
* inverse of N is assumed 0 at all times to simplify calculation. *
* Ignore all calculation of Z 2 , since the value of Z 2 does *
* not effect the result. *
* *
```

_nscale:
push
ldi
SP, FP
ldi *-FP(2),ar1
Idi @IINVERSE, r2
ldi @fftsize,rc
@mask,ar7
4,ir0
2,ir1
ldi @mid_carry,ar6
$\begin{array}{ll}\text { ldi } & 16, \operatorname{ar} 2 \\ \text { ldi } & -16, \operatorname{ar} 3 \\ \text { ldi } & 1, \operatorname{ar} 4 \\ \text { subi } & 1, r c\end{array}$
$\begin{array}{ll}\text { ldi } & 16, \operatorname{ar} 2 \\ \text { ldi } & -16, \operatorname{ar} 3 \\ \text { ldi } & 1, \operatorname{ar} 4 \\ \text { subi } & 1, r c\end{array}$
$\begin{array}{ll}\text { ldi } & 16, \text { ar2 } \\ \text { ldi } & -16, \text { ar } \\ \text { ldi } & 1, \text { ar } \\ \text { subi } & 1, r c\end{array}$
$\begin{array}{ll}\text { ldi } & 16, \text { ar2 } \\ \text { ldi } & -16, \text { ar } \\ \text { ldi } & 1, \text { ar } \\ \text { subi } & 1, r c\end{array}$
$\begin{array}{ll}\text { ldi } & 16, \operatorname{ar} 2 \\ \text { ldi } & -16, \operatorname{ar} \\ \text { ldi } & 1, \operatorname{ar} 4 \\ \text { subi } & 1, r c\end{array}$
$\begin{array}{ll}\text { ldi } & 16, \text { ar2 } \\ \text { ldi } & -16, \text { ar } \\ \text { ldi } & 1, \text { ar } \\ \text { subi } & 1, r c\end{array}$
$\begin{array}{ll}\text { rptb } & \text { nscaling } \\ \text { ldi } & \star a r 1, r 1\end{array}$
$\begin{array}{ll}\text { rptb } & \text { nscaling } \\ \text { ldi } & \text { *arl,r1 }\end{array}$
lsh ar3,r1,r7
and ar7,r1,r6
ldi $0, r 1$
ldi *+ar1,r3
; $\mathrm{r} 1<-\mathrm{Y} 1 \mathrm{YO}$
; $\mathrm{r} 7<-\mathrm{Y} 1$
; $\mathrm{r} 6<-\mathrm{Y} 0$
; $\mathrm{r} 1<-\mathrm{X} 2$ * Y1 Y0 $=0$
; $\mathrm{r} 3<-\mathrm{Y} 3 \mathrm{Y} 2$
bpd nmults ;if Y2 = 1
$\begin{array}{ll}\text { bpd } & \text { nmults } \\ \text { ldi } & \text { r2,r0 }\end{array}$
lsh ar3,r0,r5
and ar7,r0,r4
ldi
nmults: addi
$0, r 0$
ro,r1
$; \mathrm{r} 0<-\mathrm{Y} 2 * \mathrm{X} 1 \mathrm{XO}=0$
; $\mathrm{rl}<-\mathrm{X} 1 \mathrm{X0}+\mathrm{Y} 1 \mathrm{Y} 0$
$; \mathrm{r} 0<-\mathrm{Y} 2 * \mathrm{X} 1 \mathrm{XO}=0$
; $\mathrm{r} 1<-\mathrm{X} 1 \mathrm{X0}+\mathrm{Y} 1 \mathrm{Y} 0$
mpyi
r4,r6,r0
; $\mathrm{r} 0<-\mathrm{XO}$ * Y0
; $\mathrm{r} 3<-\mathrm{X} 1$ * Y0
mpyi r5,r6,r3
mpyi r7,r4
; $\mathrm{r} 4<-\mathrm{Y} 1$ * X 0
addi r4,r3 $\quad \mathrm{r} 3<-(\mathrm{X} 1$ * Y 0$)+(\mathrm{Y} 1$ * X 0$)$
;initialize registers for ; c function interface ; load argument
; load multiplication inverse of ffnt ; size
; setup repeat counter
; ar7 <- 0ffffh
ldi
ldi
ldi
ldi @mid_carry,ar6
+, 1
; constant 4
; Constant 5

FP
ldi
*-FP(2), ar1
@IINVERSE, r2
@fftsize,rc
@mask, ar7
4, ir0 ; Constant 5

```
    ;constant shift left 16 bits
;constant shift right }16\mathrm{ bits
;constant 1
```

    and
    
ldi

```
;r0 <- multiplicative inverse
;r5 <- X1
;r4<- X0
```

| bncd | nmultsnxt |  |
| :---: | :---: | :---: |
| 1 sh | ar3,r3, r4 | ; 4 <- high word of r3 |
| lsh | ar2,r3 | ;r3 <- low word of r3 left shifted |
| 16 bits |  |  |
| mpyi | r7, r5 | ; 5 <- Y1 * X1 |
| addi | ar6, r5 | ; $\mathrm{r} 5+65536$ |
| nmultsnxt: |  |  |
| addi | r3, r0 | ;r0 gets low word of product |
| and | ir0,st,r3 | ;r3 gets zero flag |
| addc | r5,r4 | ;r4 gets partial high word of |
| product |  |  |
| ldi | 0,r5 | ;r5 to receive carry over |
| addi | r4, r1 | irl gets high word of product |
| and | st, r3 | ir3 gets zero flag |
| addc | $0, \mathrm{r} 5$ | ;r5 gets carry |
| and | st.r3 | ;r3 gets zero flag |
| bnz | nscaling |  |
| not | r1 | ; $(\mathrm{AB}-1)=(\mathrm{AB})-1$, thus begin |
| residue |  |  |
| addi | r1,r0 | ;reduction |
| and | ar4,st, r1 | ; save carry |
| xor | ar4,r1 | ; complement carry |
| addi | r1, r0 | ; diminished one result |
| addi | ar4, ro | ; convert to binary |
| and | ar4,st,r1 | ; save carry |
| nscaling: |  |  |
| sti | r1,*+ar1 |  |
| \||sti | r0,*ar1++(ir1) | istore result |
| pop | FP |  |
| rets |  |  |

```
*========================================================================*****)
* IFNT using DIT FFT algorithm
*=======================================================================******)
*
* This routine performs IFNT using DIT FFT algorithm. The
* starting address of the input sequence is stored in memory
* location FP-2.
*
iffnt:
push FP
ldi
ldi
sti ar0,@_com_saddrl
ldi
ldi
@fftsize,ir1
ir1,ar4
ir1,ar6
-1,ar4
@logsize,r0
@shiftmask,ar7
;initialize registers for
;c function interface
;load argument
ldi
ldi
lsh
ldi
1di
nloopi:
    ldi
    ldi
    lsh
    r0,ar5
    ar5,r7
    1,ir0
    -1,ir1
    @_com_saddrl,ar0
    ar5,ar0,ar1
    irl,rc
    1,rc
    nloop1ni
    *ar1,*ar0,r3 ;r3 <- binary diff, low word
    *+arl,*+ar0,r4 ;r4 <- binary diff, high word
    bnnd naddli
    ldi 1,ar2
    ldi 0,ar3
    nop
    addi ar2,r3
    and
naddli: addi
    addc
    bzd nlooplni
    sti r4,*+ar1
    ||si r3,*arl++(ir0)
index
    subi ar2,r1,r3
```

;index for increment of $m$ ; $N / m$, power of 2 , \# bits to shift ; N/2, for scaling comparison ;ar6 <- N
; $\log \mathrm{N}$, number of main loops ;ar7 <- Offffffffh
; $m / 2$, index to 2nd number ; counter from $\mathrm{m} / 2-1$ to 1
; update iro, m/2
;update irl, N/m
;ar0 -> x[0]
;arl -> $x[m / 2]$
;repeat $\mathrm{N} / \mathrm{m}$ times
subi $1, r c$
rptb
subi
subb
bnnd
ldi
1, ar2
$0, \operatorname{ar} 3$
ar2,r1,r3
ar2,r3
ar2.st.r4
*ar1,*ar0,r1
*+ar1,*+ar0,r2
nloopini
sti
r3,*ar1++(ir0)
;if negative, low word is d-1, ; thus d-1 mod operation
;rl <- binary sum, low word ;r2 <- binary sum, high word ;if sum < 2^32, store result ; save high word diff ; save low word diff, and increment index

```
; convert to d-1, low word
```

subb
xor addi and
nloop1ni:
sti
||sti index
nloop2i: subi bzd ldi addi addi
ldi
subi rptb
subi subb
bnd mpyi lsh
subi
subi
bnd

1sh
lsh
xor
subi
nscalei:
lsh
or
ndonei: addi
addc
subi
subb
bnnd
ldi
ldi
nop
ar3,r2,r4
ar2.r4
r4,r3,r1
ar2,st,r2
r2,*+ar0 ; save high word sum
rl,*ar0++(ir0) ;save low word sum, and increment
; convert to $d-1$, high word
$; A+B=[(A+B)-1]+1$. Thus $d-1$
; mod operation
; save carry

; decrement r7
;ar0 -> x[0]
;ar0 $->x[k]$
;ar1 -> $x[k+m / 2]$
; repeat $\mathrm{N} / \mathrm{m}$ times
; convert to d-1 low word
; convert to d-1 high word

```
;# of bit shift
;adjust bit shift for double
;counting
;r1 <- (-r1) mod FFTSIZE
;X - N/2 shift, shift d2
```

;if shift less than $N / 2$, next shift
; X
; shift mask by X - N/2
; shift $d-1$ data by $X-N / 2$
; complement r5
; shift more than $N / 2$, adjust next ;shift

```
;X - N
;left shift X or X-N bits
;or register to get final d-1 result
;left shift \(X\) or \(X-N\) bits
```

; convert to binary low
; convert to binary high
; r3 <- binary diff, low word
; r4 <- binary diff, high word
;if diff is positive
; register ar2 <- 1
;register ar3<-0

| addi <br> and | $\begin{aligned} & \operatorname{ar} 2, r 3 \\ & \operatorname{ar} 2, s t, r 4 \end{aligned}$ | ;if negative, low word is $d-1$, ; thus d-1 mod operation |
| :---: | :---: | :---: |
| nadd2i: addi addc | $\begin{aligned} & \mathrm{r} 5, * \operatorname{ar} 0, \mathrm{r} 1 \\ & \mathrm{r} 6, * \operatorname{ar} 0, \mathrm{r} 2 \end{aligned}$ | ; $\mathrm{rl}<-\mathrm{binary}$ sum, low word <br> ;r2 <- binary sum, high word |
| bzd | nloop2ni | ;if sum < 2^32, store result |
| sti | r4,*+arl | ; save high word diff |
| \||sti | r3,*ar1++(ir0) | ; save low word diff, and increment |
| index |  |  |
| subi | ar2,r1,r3 | ; convert to d-1, low word |
| subb | ar3,r2,r4 | ; convert to d-1, high word |
| xor | ar2,r4 | $; A+B=[(A+B)-1]+1$. Thus d-1 |
| addi | r4,r3, r1 | ; mod operation |
| and | ar2,st,r2 | ; save carry |
| nloop2ni: |  |  |
| sti | r2,*+ar0 | ; save high word sum |
| \||sti | r1,*ar0++(ir0) | ; save low word sum, and increment |
| index |  |  |
| br | nloop2i |  |
| nloopni: |  |  |
| subi | 1, r0 | ;update ro, decrement |
| bnz | nloopi |  |
| pop | FP |  |
| rets |  |  |


addi
nmultnxt1:
mpyi
addi
bncd
lsh
lsh
mpyi
addi
nmultnxt2:
addi
and addc
product
addc
addi
and addc
and
bnzd
nop
nop
nop
not
addi
and
addi
addc
xor
addi
and
xor addi
and
nmloop:
sti
||sti
pop
rets
ar4, r2
r7.r4
r4, r3
nmultnxt2
ar3,r3,r4
ar2,r3
r7,r5
ar6,r5
r3,r0
ir0,st,r3
r5,r4

0,r2
r4,r1
st,r3
$0, r 2$
st, r3
nmloop
*++ar0(ir1)
*++ar1(ir1)
r1
r1,r0
ar4, st,r1
r2,r0
$0, r 1$
ar4, rl
r1, ro
ar4, st,r1
ar4, r1
r1, r0
ar4,st,r1
r1,**ar5
r0,*ar5++(ir1)
;r2 + 1 if r0+rl has carry
; $\mathrm{r} 4<-\mathrm{Y} 1$ * X 0
$; r 3<-(X 1$ * $Y 0)+(Y 1 * X 0)$
;r4 <- high word of r3
; r3 <- low word of r3 left shifted
; 16 bits
; $\mathrm{r} 5<-\mathrm{Y} 1$ * X1
$i r 5+65536$
;r0 gets low word of product
;r3 gets zero flag
;r4 gets partial high word of
;r2 gets msb
;rl gets high word of product
;r3 gets zero flag
;r2 gets msb
;r3 gets zero flag
; $(\mathrm{AB}-1)=(\mathrm{AB})-1$, thus begin ;residue
; reduction
;save carry
; add msb
; complement carry
;diminished one result
; save carry
; convert to binary
;binary result
;save carry
;store result

FP


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