Fundamentals of Signal Processing, Characteristics of Common Signals, and Applications

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***Abstract*—Signal processing serves as a fundamental technology for extracting information and optimizing systems in many application areas that include communications, radar and medical imaging. However, on the one hand, the research is not very deeply concerned with diversified application of multi-type signal characteristics, and on the other hand the adaptability of Fourier transform in complex environment or scene is not studied enough. Signal classification, including the properties of signals, Fourier Transform, and its applications are the subject of this paper, based on a mixture of theory and example cases. This paper finds that various signals (e.g., 1 5 continuous/discrete, periodic/non401 6 periodic) have different processing strategies, and Fourier Transform is capable of effectively transforming signals from time to frequency domain, it is reliable for representing information, and extracting information. This work provides theoretical proofs for cross-domain application in signal processing.**

***Keywords*—signal processing, fourier transform, signal characteristics, spectrum analysis, signal classification**

I. INTRODUCTION

In the age of smart technology, under the hood of 5G communication, medical imaging, and radar detection, signal processing is necessary. Academia has investigated the basic theories of signals and transform algorithms. For example, in the comprehensive review by Smith *et al.* [1], they systematically summarized the progress in the fundamental research of various signal transform algorithms. However, there are still some blank spots. Previous work did not sufficiently associate signal characters with application scenarios; and the practicability of Fourier Transform in complex signal restoration is not yet fully guaranteed. As pointed out by Johnson and Brown [2], current research often fails to bridge the gap between theoretical signal characteristics and the practical needs of applications such as real-time industrial monitoring and high-definition medical imaging. Moreover, their study also indicates that the effectiveness of Fourier Transform in restoring complex signals corrupted by multiple types of noise remains a subject of further exploration.

This paper focuses on “signal processing basics, common signals, and Fourier transform applications,” and explains three aspects in a declarative manner. First, it clarifies the criteria under which differences between signals can be observed and specifies the appropriate conditions required for signals that adhere to different standards. Second, it elaborates the reasons why the Fourier Transform is an ideal tool for signal processing. Third, it describes the specific working mechanisms of the Fourier Transform in common application scenarios such as spectrum analysis and filtering.

This study also applies the case analysis method (e.g., sine wave signals, digital signals, etc.) to verify the rationality of the theoretical analysis.

The importance of this study is two-fold: From the theoretical aspect, it supplements such a “characteristic-application” related analysis by incorporating the developed signal processing theory; from the practical viewpoint, it offers some suggestions for the engineering applications, e.g. design of communication filtering schemes and medical imaging restoration accuracy, which potentially serves as a solid reference for future algorithm development.

II. FUNDAMENTAL THEORIES OF SIGNAL PROCESSING

A . Definition and Classification of Signals

1) Definition of Signals

A signal is any physical quantity (such as electrical, acoustic, or color-related quantities) which conveys information over space and time. In communication, voice and text are transmitted through electrical signals; in medicine, ECG signals represent heart function. It serves as a middle ground for encoding information through amplitude modulation, frequency modulation, or phase modulation to facilitate communication between different systems [4, 5].

2) Continuous and Discrete Signals

For continuous-time signals, values are assigned at every point in time. For instance, for sound signals, their amplitudes change continuously from 0 to 1 second and can be captured by analog microphones. A discrete signal has no values at the instants between its discrete time points. Images, which are stored as pixels, have only fixed gray values in discrete coordinate points, and require an analog-to-digital converter (ADC) for sampling from continuous signals. The difference lies in the matter of continuity over time: continuous signals, which describe natural physical processes, are converted to discrete signals, which are preferred for digital storage and computation.

3) Periodic and Non-periodic Signals

A signal is said to be periodic if the signal’s waveform is repeated with a period T (where $T > 0$), and the signal satisfies $f(t+T) = f(t)$ for all t. One of the classic examples of periodic signals is sinusoidal signals, which we are all familiar with. For example, the 50 Hz AC (known as mains power in power generation systems) has a period of 0.02 seconds (since $1/50 = 0.02$ s), meaning the voltage or current repeats its waveform every 0.02 seconds. These signals are extensively used in power conditioning as well as signal sources because of their periodic recurrence properties. On the other hand, non-periodic signals do not have a specific repeating cycle; we cannot find a constant T such that $f(t + T) = f(t)$ for all integers n (i.e., $f(t + nT) = f(t)$). Human voice signals are a prime

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example: when people speak, both the frequency (pitch-related) and the acoustic amplitude (loudness- related) of the voice changes continuously according to content, tone and rhythm, so the signal is never repeated in an orderly fashion. Without project using, periodic signals can easily be decomposed and analyzed by Fourier series, which splits it into a sum of sinusoidal terms with definite frequencies, thus frequency domain analysis is convenient. In the case of nonperiodic signals, on the other hand, they are processed in the frequency domain by means of the Fourier transform, which is capable of processing aperiodic waveforms by treating them as periodic signals with a period that, in essence, tends to infinity.

4) Energy and Power Signals

A unit-average-energy (UAE) signal is a signal that has finite, non-zero total energy over the entire time domain but whose average power approaches zero, since the total energy is distributed over an infinite time duration. One example of such signals is the impulse signal, which is non-zero only at one or more points and has finite total energy (e.g., unity energy). This property is important in the analysis of system responses because impulse signals are well suited to exciting a system and revealing its dynamic characteristics. Power signals have the reverse properties - i.e., infinite total energy, but finite average power. Consider common 220V AC, for example: its total energy obviously sums to infinity since it is, so to speak, continuous (i.e., never turns off), but its average power is constant (dependent on RMS voltage). This characteristic makes power signals easily found in applications such as power transmission, for which the energy should be provided continuously, and those applications in round-the-clock surveillance that are based on steady power input.

B. Characteristics of Signals

1) Energy Characteristics

Signal energy is calculated as follows:

$$E = \int_{-\infty}^{+\infty} |f(t)|^2 dt \tag{1}$$

Differences exist: impulse signals concentrate energy at an instant, with finite energy; sinusoidal periodic signals extend infinitely in time, resulting in infinite energy. This difference enables energy threshold screening (e.g., extracting target pulses in radar signals) for energy signals, and power control for stable transmission of power signals.

$$E = \sum_{n=-\infty}^{+\infty} |f(n)|^2 \tag{2}$$

2) Power Characteristics

$$P = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} |f(t)|^2 dt \tag{3}$$

Average power is calculated as

(periodic signals) or simply as the average power of one period (e.g., for a sinusoidal signal, average power = 1/2 of the amplitude squared). In the field, power profiles are of great significance: in the field of wireless communication, one needs to limit the power of base station signal not to cause any interference and in the area of medical monitoring, if the power of the ECG is not in its normal profile, it might be a sign of a problem with the heart's rhythm signals.

C. Signal Transformation

1) Fourier Transform

Fourier Transform converts signals from time domain to frequency domain, based on the principle that "any non-periodic signal can be decomposed into superposed complex exponential signals". The continuous signal expression is

$$F'(\omega) = \int_{-\infty}^{+\infty} f(t) e^{-j\omega t} dt \tag{4}$$

where f(t) is the timederivative sinal, F(omega) is the derivative domain spectrum, and omega is in angular fruquency. Its primary application is the analysis of spectral content, or the frequency domain, of a signal: for voice signals (sound analysis), it is the frequency components; for radar, it is time to frequency reduction. The book The Fourier Transform and Its Applications provides a detailed explanation of the Fourier transform's definition formula, the derivation of the inverse transform formula, and their applications. It serves as a rigorous theoretical basis for the mathematical model formulas of the Fourier transform used in this paper [3]

2) Laplace Transform

Laplace Transform, an extension of Fourier Transform, has the expression

$$F'(s) = \int_{0}^{+\infty} f(t) e^{-st} dt \tag{5}$$

($s=\sigma+j\omega$, σ is real part). It expands the signal range (e.g., processing exponentially growing signals) and simplifies operations: differential/integral in time domain becomes algebraic operations in frequency domain, facilitating circuit transfer function solving and control system stability analysis (e.g., oscillation detection).

D. Convolution and Correlation Analysis

1) Convolution

$(f*g)(t) = \int_{-(\infty)}^{+(\infty)} f(\tau) g(t-\tau) d\tau$ Convolution describes the interaction between two signals. For continuous signals, it is for discrete signals,

$$(f*g)(n) = \sum_{k=-\infty}^{+\infty} f(k) g(n-k) \tag{6}$$

It is applied in filtering (convolving input signal with filter impulse response to suppress noise) and system response analysis (calculating output via input and system impulse response convolution).

2) Correlation Analysis

Correlation analysis measures signal similarity, including autocorrelation (same signal at different times) and cross-correlation (different signals). For continuous signals, cross-correlation is

$$R_{fg}(\tau) = \int_{-\infty}^{+\infty} f(t) g(t+\tau) dt \tag{7}$$

and autocorrelation is

$$R_f(\tau)=\int_{-\infty}^{+\infty} f(t)f(t+\tau)dt \quad (8)$$

In radar, cross-correlation of echo and transmitted signals detects targets; in communications, autocorrelation extracts synchronization information for accurate decoding.

III. Applications of Fourier Transform in Signal Processing

A. Spectrum Analysis

Spectrum analysis uses Fourier Transform to obtain frequency component distribution (amplitude/phase spectrum) of signals.

$$f(t)=A\sin(\omega_0 t+\varphi) \quad (9)$$

Taking a sinusoidal signal $\omega=\pm\omega_0$

(A=amplitude, (omega0)=angular frequency, φ=initial phase) as an example: after Fourier Transform, amplitude values (A/2) appear only at

The phase spectrum is φ at （omega=omega0） and -φ at （ omega=omega0 ）, showing its single-frequency characteristic. As a periodic signal, it has infinite energy but average power (A^2/2). Spectrum analysis locates power-concentrated frequencies, supporting harmonic detection in power grids—finding 100Hz/150Hz components indicates harmonic interference, requiring filtering.

B. Filtering

Compared to simple clipping, filtering offers more precise gain control: it can retain necessary critical signals and effectively reduce diffusion under noisy interference, rather than discarding entire signal segments. Consider digitalised voice signals, for instance, usually sampled at 8kHz (hence sampling 125 μs). By means of Fourier Transform, it is possible to observe that the "useful" components carrying voiced speech information are mainly concentrated around 300 – 3400Hz, which coincides with the human vocal frequency band. On the other hand, noise sources, such as circuit excitation, are usually found at frequency band over 4000Hz.

To remove this noise, a low-pass filter is used: in the frequency domain, it leaves the components around 300-3400Hz untouched and sets all frequency components above 4000Hz to 0. After such frequency-domain processing, the signal is inverse Fourier transformed back to the time domain. This approach effectively extracts high-frequency noise energy without damaging the core speech information, and the signal-to-noise ratio (SNR) is greatly improved. Owing to its remarkable property of helping retain useful signals and remove noise, this type of filtering is highly applicable in voice communication systems (such as telephone calls) and is also used in digital audio processing (e.g., audio recording and editing).

C. Signal Compression

Redundancies such as the periodic repetition of a signal in the time domain are used to compress data. A signal still in the same Fourier form is the form of a square wave signal (period T, amplitude A). The Fourier series of this signal consists of a fundamental wave ((f0=1/T) and odd harmonic waves, and the higher is the harmonic number, the smaller is the corresponding harmonic amplitude. The Fourier Transform yields a spectrum; by retaining only the fundamental wave and the first 3 harmonics (which represent over 90% of the total energy) and removing higher harmonics. A Fourier Transform is then performed, and an inverse Fourier Transform is used to reconstruct the signal, resulting in a recovered signal kept to its original shape but with 1/4 video data saved. It is used in JPEG image compression and video transmission as well.

D. Signal Restoration

Signal restoration reconstructs original signals from distorted ones. For a complex exponential signal $f(t)=Ae^{i(\omega_0 t+\varphi)}$

noise may cause amplitude attenuation (A→A') and phase shift (φ→φ'). Restoration steps: 1) Perform Fourier Transform on the distorted signal to identify amplitude attenuation (A'-A) and phase shift (φ'-φ); 2) Compensate amplitude (A'→A) and correct phase (φ'→φ) in frequency domain; 3) Convert back to time domain via inverse Fourier Transform. This method improves distorted signal usability, critical in radar denoising and MRI image restoration.

IV. Conclusion

This research describes various multi-dimensional signal classifications: temporally (e.g., sound signals and digital images), periodically (e.g., sinusoidal signals and human voice signals), and energetically (e.g., impulse signals and alternating current signals). Their properties determine their respective application scenarios: for example, energy signals are used for burst detection, and power signals are used for continuous communication. FT is used in the following ways: spectrum analysis for the determination of the signal frequency; filtering – to separate the useful information from useless noise; compression to reduce the amount of data by distribution of energy in the frequency space; restoration to correct values of the frequency-domain parameters.

The current research has notable limitations. First, the case studies are too limited in scope, as they only cover simple signals (e.g., sinusoidal signals and square waves)—periodic, single-frequency waveforms that fail to account for mixed multi-component signals often encountered in practical applications. A few examples include noisy mixed communication signals (i.e., communication signals with modulation and interference) and non-stationary multi-frequency biological signals (e.g., electroencephalogram (EEG) signals). Without such an analysis of complex signals, the true practical usefulness of the research is unproven. Secondly, there aren't many comparative studies between the Fourier Transform and the other major algorithms like the Wavelet Transform. The later is good at handling non-stationary signals and extracting local time-frequency characteristics, and is thus widely used in transient signal detection. What is lacking is practical guidance for users on which algorithm to apply to a specific type of data, since the performance, accuracy, and efficiency of the algorithms under different experimental conditions have not been systematically compared.

In the future, this research can be further expanded in the following three aspects: (1) When extending to complex signals, deep learning techniques (e.g., convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep neural networks (DNNs)) will be introduced to enable automatic feature extraction, signal classification, and adaptive processing—thereby enhancing the intelligence of signal processing systems; (2) Develop a scenario-based algorithm selection model; (3) Explore cross-disciplinary applications (e.g., using signal processing techniques to secure quantum state transfer in quantum communication, or to improve the sensing precision of marine vehicles in autonomous navigation) — thus translating theoretical research into practical equipment operation.

Conflict of Interest

The author declares no conflict of interest.

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