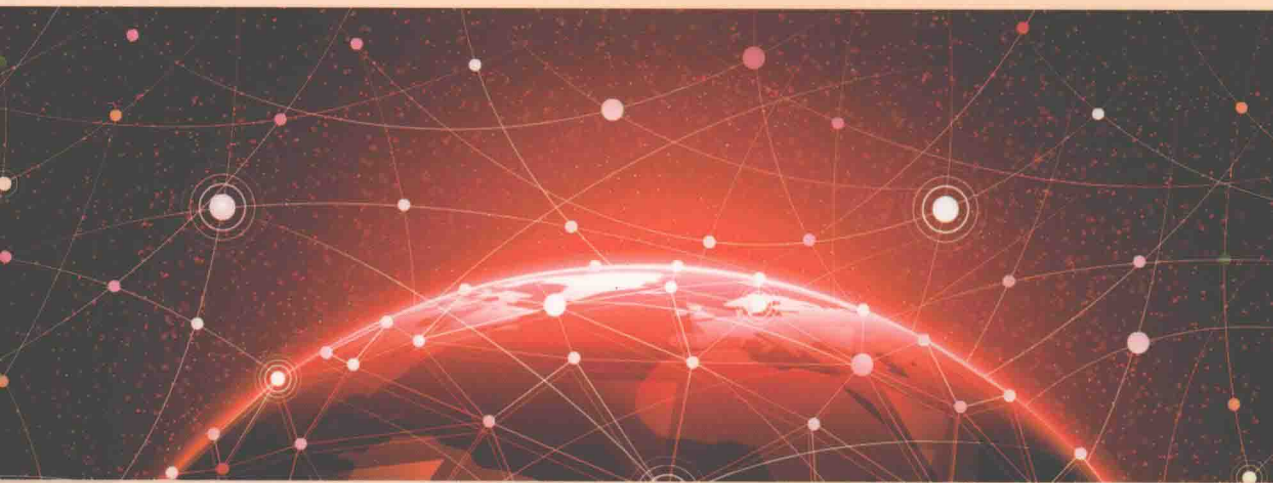

Science and Technology English for Information and
Communication Engineering

信息与通信工程 专业英语

王 桐 姜 弢◎主编



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信息与通信工程专业英语

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Communication Engineering*

王 桐 姜 弢 主 编

陈立伟 刘 露 副主编



内 容 简 介

本书由3个主题单元构成,包括19章课文。第1主题单元介绍了信号分析与处理的基本知识,其中包括信号与系统、数字信号处理、随机过程等有关课程中常用的一些基本概念,并对部分词汇做了注释。第2主题单元介绍了通信工程的基本知识,其中包括通信系统、通信网络等基础内容,也包括无线自组织网络、软件无线电、智能天线系统、蓝牙技术及4G无线通信等进阶内容。第3主题单元介绍了水声工程及信息技术中的前沿内容,包括自组织网络、大数据、图像处理等。

本书可供信息与通信工程专业学生及水声工程专业学生使用,也可供从事相关专业科研和工程技术人员参考。

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前 言

本书旨在通过教学和实践过程,使学生在原有公共英语水平的基础上,掌握专业英文文献阅读的技巧、方法和常用专业英语词汇,提高专业英文文献的阅读水平;使学生基本能够直接阅读和学习相关专业的英文资料,有能力通过阅读获取有关专业的信息和新知识,巩固和加深已有专业知识,了解本学科的发展前沿及国外本学科领域的发展趋势,提高自身专业知识的深度和广度,提高学习掌握国际前沿知识的能力。

本书涉及电子信息工程专业、通信工程专业及水声工程专业的部分专业课程内容,强调了对信号分析与处理理论的基本概念、公式和定理的说明解释,使学生能够掌握本专业的常用英文词汇,了解一些新技术的概念和发展趋势。

本书主要由哈尔滨工程大学王桐(1~6章、16~19章)、姜弢(7章、13~15章)、陈立伟(8章、9章、10章)和哈尔滨理工大学刘露(11章、12章)编写;哈尔滨工程大学田坦老师,硕士研究生崔子平、孙博、王宇、李鑫等人参与了本书部分内容的编写工作,在此一并致谢。

限于编者水平,对于书中出现的一些错误和不足之处,敬请读者批评指正。

编者

2018年7月

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Part I Signal Processing

Chapter 1 Periodic Signals

1.1 Time-domain Descriptions

The fact that the great majority of functions which may usefully be considered as signals are functions of time leads justification to the treatment of signal theory in terms of time and of frequency. A periodic signal will therefore be considered to be one which repeats itself exactly every T seconds, where T is called the period of the signal waveform; the theoretical treatment of periodic waveforms assumes that this exact repetition is extended throughout all time, both past and future. In practice, of course, signals do not repeat themselves indefinitely. Nevertheless, a waveform such as the output voltage of a mains rectifier prior to smoothing does repeat itself very many times, and its analysis as a strictly periodic signal yields valuable results. In other cases, such as the electrocardiogram, the waveform is quasi-periodic and may usefully be treated as truly periodic for some purpose. It is worth noting that a truly repetitive signal is of very little interest in a communication channel, since no further information is conveyed after the first cycle of the waveform has been received. One of the main reasons for discussing periodic signals is that a clear understanding of their analysis is a great help when dealing with periodic and random ones.

A complete time-domain description of such a signal involves specifying its value precisely at every instant of time. In some cases this may be done very simply using mathematical notation. Fortunately, it is in many cases useful to describe only certain aspects of a signal waveform, or to represent it by a mathematical formula which is only approximate. The following aspects might be relevant in particular cases:

- (1) the average value of the signal.
- (2) the peak value reached by the signal.
- (3) the proportion of the total time spent between value a and b .
- (4) the period of the signal.

If it is desired to approximate the waveform by a mathematical expression, such techniques as a polynomial expansion, a Taylor series, or a Fourier series may be used. A polynomial of order n having the form

$$f(t) = a_0 + a_1t + a_2t^2 + a_3t^3 + \cdots + a_nt^n \quad (1-1)$$

may be used to fit the actual curve at $(n+1)$ arbitrary points. The accuracy of fit will generally improve as the number of polynomial terms increases. It should also be noted that the error between the true signal waveform and the polynomial will normally become very large away from the region of the fitted points, and that the polynomial itself cannot be periodic. Whereas a polynomial approximation fits the actual waveform at a number of arbitrary points, the alternative Taylor series approximation provides a good fit to a smooth continuous waveform in the vicinity of

one selected point. The coefficients of the Taylor series are chosen to make the series and its derivatives agree with the actual waveform at this point. The number of terms in the series determines to what order of derivative this agreement will extend, and hence the accuracy with which series and actual waveform agree in the region of the point chosen. The general form of the Taylor series for approximating a function $f(t)$ in the region of the point is given by

$$f(t) = f(a) + (t - a) \times \frac{df(a)}{dt} + \frac{(t - a)^2}{2!} \times \frac{d^2f(a)}{dt^2} + \cdots + \frac{(t - a)^n}{n!} \times \frac{d^n f(a)}{dt^n} \quad (1-2)$$

Generally speaking, the fit to the actual waveform is good in the region of the point chosen, but rapidly deteriorates to either side. The polynomial and Taylor series descriptions of a signal waveform are therefore only to be recommended when one is concerned to achieve accuracy over a limited region of the waveform. The accuracy usually decreases rapidly away from this region, although it may be improved by including additional terms (so long as t lies within the region of convergence of the series). The approximations provided by such methods are never periodic in form and cannot therefore be considered ideal for the description of repetitive signals.

By contrast the Fourier series approximation is well suited to the representation of a signal waveform over an extended interval. When the signal is periodic, the accuracy of the Fourier series description is maintained for all time, since the signal is represented as the sum of a number of sinusoidal functions, which are themselves periodic. Before examining in detail the Fourier series method of representing a signal, the background to what is known as the ‘frequency-domain’ approach will be introduced.

1.2 Frequency-domain Descriptions

The basic conception of frequency-domain analysis is that a waveform of any complexity may be considered as the sum of a number of sinusoidal waveforms of suitable amplitude, periodicity, and relative phase. A continuous sinusoidal function ($\sin \omega t$) is thought of as a ‘single frequency’ wave of frequency ω radians/second, and the frequency-domain description of a signal involves its breakdown into a number of such basic functions. This is the method of Fourier analysis.

There are a number of reasons why signal representation in terms of a set of component sinusoidal waves occupies such a central role in signal analysis. The suitability of a set of periodic functions for approximating a signal waveform over an extended interval has already been mentioned, and it will be shown later that the use of such techniques causes the error between the actual signal and its approximation to be minimized in a certain important sense. A further reason why sinusoidal functions are so important in signal analysis is that they occur widely in the physical world and are very susceptible to mathematical treatment; a large and extremely important class of electrical and mechanical systems, known as ‘linear systems’, responds sinusoidally when driven by a sinusoidal disturbing function of any frequency. All these manifestations of sinusoidal function in the physical world suggest that signal analysis in sinusoidal terms will simplify the problem of relating a signal to underlying physical causes, or to the physical properties of a system

or device through which it has passed. Finally, sinusoidal functions form a set of what are called ‘orthogonal function’, the rather special properties and advantage of which will now be discussed.

1.3 Orthogonal Functions

1.3.1 Vectors and signals

A discussion of orthogonal functions and of their value for the description of signals may be conveniently introduced by considering the analogy between signals and vectors. A vector is specified both by its magnitude and direction, familiar examples being force and velocity. Suppose we have two vectors V_1 and V_2 ; geometrically, we define the component of vector V_1 along vector V_2 by constructing the perpendicular from the end of V_1 onto V_2 . We then have

$$V_1 = C_{12} V_2 + V_e \quad (1-3)$$

where vector V_e is the error in the approximation. Clearly, this error vector is of minimum length when it is drawn perpendicular to the direction of V_2 . Thus we say that the component of vector V_1 along vector V_2 is given by $C_{12} V_2$, where C_{12} is chosen such as to make the error vector as small as possible. A familiar case of an orthogonal vector system is the use of three mutually perpendicular axes in co-ordinate geometry.

There basic ideas about the comparison of vectors may be extended to signals. Suppose we wish to approximate a signal $f_1(t)$ by another signal or function $f_2(t)$ over a certain interval $t_1 < t < t_2$; in other words

$$f_1(t) \approx C_{12} f_2(t) \quad \text{for } t_1 < t < t_2$$

We wish to choose C_{12} to achieve the best approximation. If we define the error function

$$f_e(t) = f_1(t) - C_{12} f_2(t) \quad (1-4)$$

it might appear at first sight that we should choose C_{12} so as to minimize the average value of $f_e(t)$ over the chosen interval. The disadvantage of such an error criterion is that large positive and negative errors occurring at different instants would tend to cancel each other out. This difficulty is avoided if we choose to minimize the average squared-error, rather than the error itself (this is equivalent to minimizing the square root of the mean-squared error, or ‘r. m. s’ error). Denoting the average of $f_e^2(t)$ by ε , we have

$$\begin{aligned} \varepsilon &= \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} f_e^2(t) dt \\ &= \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} [f_1(t) - C_{12} f_2(t)]^2 dt \end{aligned} \quad (1-5)$$

Differentiating with respect to C_{12} and putting the resulting expression equal to zero gives the value of C_{12} for which is a minimum⁴. Thus

$$\frac{d}{dC_{12}} \left\{ \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} [f_1(t) - C_{12} f_2(t)]^2 dt \right\} = 0$$

Expanding the bracket and changing the order of integration and differentiating gives

$$C_{12} = \int_{t_1}^{t_2} f_1(t)f_2(t)dt / \int_{t_1}^{t_2} f_2^2(t)dt \quad (1-6)$$

1.3.2 Signal description by sets of orthogonal functions

Suppose that we have approximated a signal $f_1(t)$ over a certain interval by the function $f_2(t)$ so that the mean square error is minimized, but that we now wish to improve the approximation. It will be demonstrated that a very attractive approach is to express the signal in terms of a set of functions $f_2(t), f_3(t), f_4(t)$, etc., which are mutually orthogonal. Suppose the initial approximation is

$$f_1(t) \approx C_{12}f_2(t) \quad (1-7)$$

and that the error is further reduced by putting

$$f_1(t) \approx C_{12}f_2(t) + C_{13}f_3(t) \quad (1-8)$$

where $f_2(t)$ and $f_3(t)$ are orthogonal over the interval of interest. Now that we have incorporated the additional term $C_{13}f_3(t)$, it is interesting to find what the new value of C_{12} must be in order that the mean square error is again minimized. We now have

$$f_e(t) = f_1(t) - C_{12}f_2(t) - C_{13}f_3(t) \quad (1-9)$$

and the mean square error in the interval $t_1 < t < t_2$ is therefore

$$\varepsilon = \frac{1}{(t_2 - t_1)} \int_{t_1}^{t_2} [f_1(t) - C_{12}f_2(t) - C_{13}f_3(t)]^2 dt \quad (1-10)$$

Differentiating partially with respect to C_{12} to find the value of C_{12} for which the mean square error is again minimized, and changing the order of differentiation and integration, we have again

$$C_{12} = \int_{t_1}^{t_2} f_1(t)f_2(t)dt / \int_{t_1}^{t_2} f_2^2(t)dt \quad (1-11)$$

In other words, the decision to improve the approximation by incorporating an additional term $f_3(t)$ in does not require us to modify the coefficient, provided that $f_3(t)$ is orthogonal to $f_2(t)$ in the chosen time interval. By precisely similar arguments we could show that the value of C_{13} would be unchanged if the signal were to be approximated by $f_3(t)$ alone.

This important result may be extended to cover the representation of a signal in terms of a whole set of orthogonal functions. The value of any coefficient does not depend upon how many functions from the complete set are used in the approximation, and is thus unaltered when further terms are included. The use of a set of orthogonal functions for signal description is analogous to the use of three mutually perpendicular (that is, orthogonal) axes for the description of a vector in three-dimensional space, and gives rise to the notion of a 'signal space'. Accurate signal representation will often require the use of many more than three orthogonal functions, so that we must think of a signal within some interval $t_1 < t < t_2$ as being represented by a point in a multidimensional space.

To summarize, there are a number of sets of orthogonal functions available such as the so-called Legendre polynomials and Walsh functions for the approximate description of signal waveform, of which the sinusoidal set is the most widely used. Sets involving polynomials in t are not by their very nature periodic, but may sensibly be used to describe one cycle (or less) of a

periodic waveform; outside the chosen interval, errors between the true signal and its approximation will normally increase rapidly. A description of one cycle of a periodic signal in terms of sinusoidal functions will, however, be equally valid for all time because of the periodic nature of every member of the orthogonal.

1.4 The Fourier Series

The basis of the Fourier series is that a complex periodic waveform may be analysed into a number of harmonically related sinusoidal waves which constitute an orthogonal set. If we have a periodic signal $f(t)$ with a period equal to T , then $f(t)$ may be represented by the series

$$f(t) = A_0 + \sum_{n=1}^{\infty} A_n \cos n\omega_1 t + \sum_{n=1}^{\infty} B_n \sin n\omega_1 t \quad (1-12)$$

where $\omega_1 = 2\pi/T$. Thus $f(t)$ is considered to be made up by the addition of a steady level (A_0) to a number of sinusoidal and cosinusoidal waves of different frequencies. The lowest of these frequencies is ω_1 (radians per second) and is called 'the fundamental'; waves of this frequency have a period equal to that of the signal. Frequency $2\omega_1$ is called 'the second harmonic', $3\omega_1$ is 'the third harmonic', and so on. Certain restrictions, known as the Dirichlet conditions, must be placed upon $f(t)$ for the above series to be valid. The integral $\int |f(t)| dt$ over a complete period must be finite, and may not have more than a finite number of discontinuities in any finite interval. Fortunately, these conditions do not exclude any signal waveform of practical interest.

1.4.1 Evaluation of the coefficients

We now turn to the question of evaluating the coefficients A_0 , A_n and B_n . Using the minimum square error criterion described in foregoing text, and writing for the sake of convenience, we have

$$\left. \begin{aligned} A_0 &= \frac{1}{2\pi} \int_{-\pi}^{\pi} f(x) dx \\ A_n &= \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos nx dx \\ B_n &= \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \sin nx dx \end{aligned} \right\} \quad (1-13)$$

Although in the majority of cases it is convenient for the interval of integration to be symmetrical about the origin, any interval equal in length to one period of the signal waveform may be chosen.

Many waveform of practical interest are either even or odd functions of time. If $f(t)$ is even then by definition $f(t) = f(-t)$, whereas if it is odd $f(t) = -f(-t)$. If $f(t)$ is even and we multiply it by the odd function $\sin n\omega_1 t$ the result is also odd. Thus the integrand for every B_n is odd. Now when an odd function is integrated over an interval symmetrical about $t=0$, the result is always zero. Hence all the B coefficients are zero and we are left with a series containing only

cosines. By similar arguments, if $f(t)$ is odd the A coefficients must be zero and we are left with a sine series. It is indeed intuitively clear that an even function can only be built up from a number of other functions which are themselves even, and vice versa.

We have already seen how the Fourier series is simplified in the case of an even or odd function, by losing either its sine or its cosine terms. A different type of simplification occurs in the case of a waveform possessing what is known as 'half-wave symmetry'. In mathematical terms, half-wave symmetry exists when

$$f(t) = -f(t + T/2) \quad (1-14)$$

In other words any two values of the waveform separated by $T/2$ will be equal in magnitude and opposite in sign. Generalizing, only odd harmonics exhibit half-wave symmetry, and therefore a waveform of any complexity which has such symmetry cannot contain even harmonic components. Conversely, a waveform known to contain any second, fourth, or other harmonic components cannot display half-wave symmetry.

Usually, we have always integrated over a complete cycle to derive the coefficients. However in the case of an odd or even function it is sufficient, and often simpler, to integrate over only one half of the cycle and to multiply the result by 2. Furthermore if the wave is not only even or odd but also displays half-wave symmetry, it is enough to integrate over one quarter of a cycle and multiply by 4. These closer limits are adequate in such cases the function that is being integrated is repetitive, repeating twice within one period when the function is either even or odd, and four times within one period when it also exhibits half-wave symmetry.

1.4.2 Choice of time origin, and waveform power

The amount of work involved in calculating the Fourier series coefficients for a particular waveform shape is reduced if the waveform is either even or odd, and this may often be arranged by a judicious choice of time origin (that is, shift of time origin). This shift has therefore merely had the effect of converting a Fourier series containing only sine terms into one containing only cosine terms; the amplitude of a component at any one frequency is, as we would expect, unaltered. For a complicated waveform which is neither even nor odd, it must be expected to include both sine and cosine terms in its Fourier series.

As the time origin of a waveform is shifted, the various sine and cosine coefficients of its Fourier series will change, but the sum of the squares of any two coefficients A_n and B_n will remain constant, which means that the average power of the waveform, a concept familiar to electrical engineers, is unaltered.

The above ideas lead naturally to an alternative trigonometric form for the Fourier series. If the two fundamental components of a waveform are

$$A_1 \cos \omega_1 t \text{ and } B_1 \sin \omega_1 t$$

their sum may be expressed in an alternative form using trigonometric identities

$$A_1 \cos \omega_1 t + B_1 \sin \omega_1 t = \sqrt{(A_1^2 + B_1^2)} \cos \left(\omega_1 t - \tan^{-1} \frac{B_1}{A_1} \right)$$

$$= \sqrt{(A_1^2 + B_1^2)} \sin\left(\omega_1 t + \tan^{-1} \frac{B_1}{A_1}\right) \quad (1-15)$$

Thus the sine and cosine components at a particular frequency are expressed as a single cosine or sine wave together with a phase shift. If this procedure is applied to all harmonic components of the Fourier series, we get the alternative forms

$$f(t) = A_0 + \sum_{N=1}^{\infty} C_n \cos(m\omega_1 t - \phi_n) \text{ or}$$

$$f(t) = A_0 + \sum_{N=1}^{\infty} C_n \sin(n\omega_1 t + \theta_n) \quad (1-16)$$

where

$$C_n = \sqrt{A_n^2 + B_n^2}; \phi_n = \tan^{-1} B_n/A_n; \theta_n = \tan^{-1} A_n/B_n \quad (1-17)$$

Finally, we note that since the mean power represented by any component wave is

$$(A_n^2 + B_n^2)/2 = C_n^2/2 \quad (1-18)$$

and the power represented by the term A_0 is simply A_0^2 , the total average waveform power is equal to

$$P = A_0^2 + \frac{1}{2} \sum_{n=1}^{\infty} C_n^2 \quad (1-19)$$

But P may be expressed as the average value over one period of $[f(t)]^2$ using the convention that is considered to represent a voltage waveform applied across a 1 ohm resistor. Hence

$$P = A_0^2 + \frac{1}{2} \sum_{n=1}^{\infty} C_n^2 = \frac{1}{T} \int_{-T/2}^{T/2} [f(t)]^2 dt \quad (1-20)$$

This result is a version of a more general one known as Parseval's theorem, and shows that the total waveform power is equal to the sum of the powers represented by its individual Fourier components. It is, however, important to note that this is only true because the various component waves are drawn from an orthogonal set.

词 汇

accuracy	<i>n.</i> 精确性, 准确度, 精度
amplitude	<i>n.</i> 振幅, 幅度
aperiodic	<i>adj.</i> 非周期的
approach	<i>n.</i> 接[逼]近; 近似法[值]; 途径, 方法
approximation	<i>n.</i> 近似值
arbitrary	<i>adj.</i> 任意的
channel	<i>n.</i> 信道, 频道
coefficient	<i>n.</i> 系数
convergence	<i>n.</i> 收敛
conversely	<i>adj.</i> 相反的, 逆的
coordinate	<i>n.</i> 坐标[系]