

## *Chapter 3*

### **Walsh Transformation**

#### **IIIA Definition of the Walsh transform**

The definition for the Walsh functions given in Section II A may be restated by saying that every function  $f(t)$  which is integrable (in the Lebesgue sense) is capable of being represented by a Walsh series defined over the open interval  $(0, 1)$  as

$$x(t) = a_0 + a_1 \text{WAL}(1, t) + a_2 \text{WAL}(2, t) + \dots \quad (3.1)$$

where the coefficients are given by

$$a_k = \int_0^1 f(t) \text{WAL}(k, t) dt \quad (3.2)$$

From this we are able to define a transform pair,

$$f(t) = \sum_{k=0}^{\infty} F(k) \text{WAL}(k, t) \quad (3.3)$$

$$F(k) = \int_0^1 f(t) \text{WAL}(k, t) dt \quad (3.4)$$

This definition applies to a continuous function limited in time over the interval  $0 \leq t \leq 1$ . For numerical use it is convenient to consider a discrete series of  $N$  terms set up by sampling the continuous functions at  $N$  equally spaced points over the open interval  $(0, 1)$ . In order that the properties of the continuous and discrete systems should correspond then we must make  $N$  equal to a power of 2, i.e.  $N = 2^p$ .

The integration shown in equation (3.4) may then be replaced by summation, using the trapezium rule on  $N$  sampling points,  $x_i$ , and we can write the discrete Walsh transform pair as

$$X_n = \frac{1}{N} \sum_{i=0}^{N-1} x_i \text{WAL}(n, i) \quad n = 0, 1, 2 \dots N-1 \quad (3.5)$$

$$x_i = \sum_{n=0}^{N-1} X_n \text{WAL}(n, i) \quad i = 0, 1, 2 \dots N-1 \quad (3.6)$$

Similar transforms,  $X_c(k)$  and  $X_s(k)$  can be obtained for a time series,  $x_i$  using Harmuth's CAL and SAL functions viz.

$$X_c(k) = \frac{1}{N} \sum_{i=0}^{N-1} x_i \text{CAL}(k, i) \quad (3.7)$$

$$X_s(k) = \frac{1}{N} \sum_{i=0}^{N-1} x_i \text{SAL}(k, i) \quad (3.8)$$

As with their functions the transforms are linear so that if

$$x_i \leftrightarrow X_n \quad \text{and} \quad y_i \leftrightarrow Y_n$$

$$ax_i + by_i \leftrightarrow aX_n + bY_n$$

where  $a$  and  $b$  are real constants and  $\leftrightarrow$  denotes a transform operator.

Also the transform is symmetrical (equation 2.2). Since  $\text{WAL}(n, i)$  is symmetrical about the mid-point of the sequence,  $i = 0, 1, 2 \dots N-1$  when  $n$  is even, and anti-symmetric when  $n$  is odd, then it also follows from equation (2.1) that a sequence  $x_i$  will have a transform composed only of even-order Walsh function coefficients (CAL function) if it is symmetric about its mid-point and be composed only of odd-order (SAL function) coefficients if the series is inversely symmetric.

### Comparison with the discrete Fourier transform

The transform and its inverse given by equations (3.5) and (3.6) may be obtained by matrix multiplication using the digital computer. Since the

matrices are symmetrical for the Walsh transform (unlike the Fourier transform) then both transform and inverse transform are identical, except for a scaling factor,  $1/N$ .

If we compare equation (3.5) with the corresponding discrete Fourier transform

$$X_f = \frac{1}{N} \sum_{i=0}^{N-1} x_i \exp(-j2\pi if/N) \quad f = 0, 1, 2, \dots, N-1 \quad (3.9)$$

we note that whilst  $\text{WAL}(n, i)$  is real and limited to values  $\pm 1$  the kernel,  $K = \exp(-j2\pi if/N)$ , is complex and can assume  $N$  different values for each coefficient. As a direct consequence of this the Walsh transform proves considerably easier and faster to calculate using digital methods.

It may also be noted that since the sine and cosine functions cannot be represented exactly by a finite number of bits then a source of truncation noise is introduced by the discrete Fourier transform which involves repeated multiplication by a complex number. The Walsh transform, on the other hand, involves only addition and subtraction and precise representation is possible, so that the transform is not a noisy one.

### IIIC Effects of circular time shift

The discrete Fourier transform is invariant to the phase of the input signal so that the same spectral decomposition can be obtained independently of the phase or circular time-shift of the input signal. This is not the case for the discrete Walsh transform.

Walsh transform signals conform to Parseval's theorem where the energy in the time and frequency domains are shown to be equivalent. Expressing this energy in terms of the sum of the squared coefficients for a discrete time series,  $x_i$ , and its transformed coefficients,  $X_n$ , a special and simplified case of Parseval's theorem may be expressed as

$$\frac{1}{N} \sum_{i=0}^{N-1} (x_i)^2 = \sum_{n=0}^{N-1} (X_n)^2 \quad (3.10)$$

If the transformed coefficients,  $X_n$ , are expressed terms of CAL and SAL transformed coefficients (see Section VE), we can also write

$$\begin{aligned} \frac{1}{N} \sum_{i=0}^{N-1} x_i^2 &= X_i^2(0, t) + \sum_{k=1}^{N/2-1} (X_c^2(k, t)) + \sum_{k=1}^{N/2-1} (X_s^2(k, t)) + X_s^2(N/2, t) \\ k &= 1, 2, \dots, (N/2-1) \\ i &= 0, 1, 2, \dots, (N-1) \\ 0 &\leq t \leq 1 \end{aligned} \quad (3.11)$$

where  $X_c(k, t)$  and  $X_s(k, t)$  are the CAL and SAL function coefficients for  $x_i$ .  
Now  $x_i$  is circularly-shifted forming

$$y_i = x_{i+p} \quad (3.12)$$

as noted by Whelchel and Guinn<sup>1</sup>,

$$Y_c^2(k, t) + Y_s^2(k, t) \neq X_c^2(k, t) + X_s^2(k, t) \quad (3.13)$$

However, Pichler<sup>2</sup> has shown that if the time-shift is obtained through a dyadic translation,

$$z_i = x_{i \oplus p} \quad (3.14)$$

where  $\oplus$  indicates Modulo-2 addition for the binary representations of  $i$  and  $p$  then

$$Z_c^2(k, t) + Z_s^2(k, t) = X_c^2(k, t) + X_s^2(k, t) \quad (3.15)$$

The sequence spectrum is invariant under dyadic time-shift of the input signal. This also indicates that a relationship must exist between the sequence values obtained, namely

$$Z(k, t) = X(k \oplus p, t) \quad (3.16)$$

This is shown in the following example.

0	0.663	0.063	0	0	-0.263	0.025	0
0	-0.052	-0.006	0	0	-0.126	0.013	0
0	-0.013	-0.002	0	0	0.006	0	0
0	-0.025	-0.002	0	0	-0.062	0.006	0

TABLE 3.1 (a). Walsh transform coefficients for a simple sine waveform.  $N = 32$ .

0	-0.063	0.663	0	0	0.025	0.263	0
0	0.006	-0.052	0	0	0.013	0.126	0
0	0.001	-0.013	0	0	0	-0.006	0
0	0.002	-0.025	0	0	0.006	0.062	0

TABLE 3.1 (b). Walsh transform coefficients for the sine waveform shifted by  $90^\circ$ .

Table 3.1 shows the discrete Walsh transform of a single cycle of a sampled sinusoidal waveform having 32 values, which is compared with a transform of the same waveform circularly-shifted through  $\pi/2$  radians. If we take the shift index,  $p$ , as  $p = \log_2 8 = 3$ , then we obtain the following complex values for the sequence coefficients  $k$  and  $k \oplus p$ :

### Conversion between discrete Walsh and Fourier transformation

In equations (3.6) and (3.9) we can express a sampled time series,  $x_i$ , of  $N$ , in terms of its Fourier transform series,  $X_f$ , or its Walsh transform series,  $X_n$ , viz.

$$x_i = \sum_{f=0}^{N-1} X_f \exp(j2\pi if/N) = \sum_{n=0}^{N-1} X_n \text{WAL}(n, i) \quad (3.26)$$

where  $f, i, n = 0, 1, \dots, (N-1)$ .

Hence conversion from Fourier to Walsh transformation is

$$\begin{aligned} X_n &= \frac{1}{N} \sum_{i=0}^{N-1} x_i \text{WAL}(n, i) \\ &= \frac{1}{N} \sum_{f=0}^{N-1} X_f \left( \sum_{i=0}^{N-1} \text{WAL}(n, i) \exp(j2\pi if/N) \right) \end{aligned} \quad (3.27)$$

conversion from Walsh to Fourier transformation is

$$\begin{aligned} X_f &= \frac{1}{N} \sum_{i=0}^{N-1} x_i \exp(-j2\pi if/N) \\ &= \frac{1}{N} \sum_{n=0}^{N-1} X_n \left( \sum_{i=0}^{N-1} \text{WAL}(n, i) \exp(-j2\pi if/N) \right) \end{aligned} \quad (3.28)$$

A limitation here is, of course, that  $N$  be sufficiently large so that an accurate representation of the sampled time series is possible from a limited number of terms. This was discussed in Section II F where the number of terms required was shown to be dependent on the shape of the original continuous time function,  $f(t)$ .

### Summary of Walsh transform characteristics

The characteristics of the Walsh function and its transform described in the preceding text are compared with the Fourier function and summarised in Table 3.3. The relationships given refer to a discrete time series where the number of terms  $N$  is expressed as a power of 2.

If we consider the discrete Walsh transform, given by equation (3.5), as a Walsh function matrix obtained by sampling the continuous function of equation (3.4) then the relationship

$$\mathbf{W} \cdot \mathbf{W}^{-1} = \mathbf{W}^{-1} \cdot \mathbf{W} = N \cdot \mathbf{I} \quad (3.29)$$

thus applies.

Here  $\mathbf{W}$  and  $\mathbf{W}^{-1}$  are the direct and transposed Walsh function matrix and  $\mathbf{I}$  is an identity matrix (i.e. an  $N$  by  $N$  unit matrix). This derives from a general property of the Hadamard matrix (discussed in Chapter 2) which is related simply to the Walsh matrix by means of a permutation of the rows. The Walsh matrix is a symmetrical matrix. The relationship given in equation (3.29) is fundamental to the derivation of the fast Walsh transform which is examined in the next section.

### IIIH The fast Walsh transform

The basis for efficient implementation of the transformations discussed here is the high degree of redundancy present in the transform matrix. If this redundancy can be removed by using matrix factorisation then the efficiency of transformation will be improved. Such a technique was described by Good<sup>5</sup> and has resulted in the development of a fast Fourier transform (F.F.T.)<sup>6</sup>. Similar computation algorithms are available for many other orthogonal transformations including the Walsh and Haar transforms.

Computation of the discrete Walsh transform given in equation (3.29) requires  $N^2$  mathematical operations, where an operation is either an addition or a subtraction. Using matrix factorisation techniques an algorithm may be found to enable the transformation to be carried out using only  $N \log_2 N$  operations. This is known as the fast Walsh transform (F.W.T.).

A procedure for obtaining a fast Walsh transform algorithm is described in this section. This follows the well-known Cooley-Tukey algorithm used for fast Fourier transformation<sup>6</sup> and has similar limitations. In particular the value of  $N$  must be a power of two which will be seen later to be an essential condition for the factorisation method used in the algorithm. It is worth noting that certain fast Fourier transform programs may be converted to a Walsh transform by simply setting all the trigonometric values to  $\pm 1$  and removing the complex part of the transformation (since the Walsh transform is a real one). The ordering of the Walsh functions obtained with this method will, however, correspond to natural order or bit-reversed natural order.

#### IIIH1 Sequency-ordered transforms

A derivation of a fast Walsh transform algorithm having sequency-ordered coefficients is most conveniently obtained from the continued product representation given by Pratt *et al.*<sup>7</sup>. This was defined earlier for a series

$= 2^p$  terms as

$$\text{WAL}(n, i) = \prod_{r=0}^{p-1} (-1)^{n_{p-1-r}(i_r + i_{r+1})}$$

$$i, n = 0, 1, 2 \dots N-1$$

$$r = 0, 1, 2 \dots p \quad (3.30)$$

where  $i, n$  are expressed in terms of their binary digits,  $i_r$  and  $n_r$ , e.g.

$$i = (i_{p-1}, i_{p-2} \dots i_1, i_0)_2 \quad (3.31)$$

The algorithm is developed by substitution of equation (3.30) into equation (3.5) and factorising the calculation into  $p$  separate stages. Carrying out this substitution we obtain a product-sum expression for the discrete Walsh transform as,

$$X_n = \sum_{i=0}^{N-1} x_i \text{WAL}(n, i) = \prod_{r=0}^{p-1} \sum_{i_r=0}^1 (-1)^{n_{p-1-r}(i_r + i_{r+1})} x_{(i_{p-1} \dots i_0)} \quad (3.32)$$

(neglecting scaling by  $N$ ).

Here  $x_i$  is expressed as  $x_{(i_{p-1} \dots i_0)}$  and  $X_n$  is expressed as  $X_{(n_{p-1} \dots n_0)}$  where  $i_p$  and  $n_p$  are the binary bits of  $i$  and  $n$  with  $r = 0, 1, 2 \dots p$ .

The calculation of the fast Walsh transform is carried out in a series of stages, one stage for each power of 2 for  $N$ . The first calculation stage is to derive a partial transformation series,  $A_n$ , from the input series,  $x_i$ , by placing  $i_0 = 0$  in equation (3.32) giving

$$A(n_{p-1}, i_{p-1} \dots i_1) = \sum_{i_0=0}^1 (-1)^{n_{p-1}(i_0 + i_1)} x_{(i_{p-1} \dots i_0)} \quad (3.33)$$

To see how this is calculated the case of  $N = 16$  can be studied. We take the first adjacent pair of data samples and look at the  $i_1$  bit in  $x_i$ . Four values

$$(-1)^{n_{p-1}(i_0 + i_1)} \quad \text{for } i_0 = 0 \text{ or } 1$$

$$n_{p-1} = 0 \text{ or } 1$$

are obtained.

These indicate whether to add or subtract the two adjacent values of  $x_i$  and  $x_{i+1}$  (where  $i$  and  $i+1$  are decimal values). From these sums and differences the two intermediate transformed values are obtained as

$$x_i + x_{i+1}$$

and either

$$x_i - x_{i+1} \quad \text{or} \quad x_{i+1} - x_i$$

depending on the sign for  $(-1)^{n_{p-1}(i_0+i_1)}$  worked out earlier. This process is continued for the remaining consecutive pairs of  $x_i$  coefficients.

Further stages of calculation proceed serially by using the results of the preceding stage as input for the next stage. This may be expressed in the general expression for the intermediate transformation as

$$\begin{aligned} A_r(n_{p-1}, n_{p-2}, \dots, n_{p-r}; i_{p-1}, i_{p-2}, \dots, i_r) \\ = \sum_{i_{r-1}=0}^1 (-1)^{n_{p-r}(i_r+i_{r-1})} A_{r-1}(n_{p-1} \dots n_{p-r+1}, i_{p-1} \dots i_{r-1}) \end{aligned} \quad (3.34)$$

with the values of  $A_1$  to  $A_p$  retained in temporary storage during the course of the calculation.

Finally we need to normalise the result through division by  $N$ , viz.

$$X_{(n_{p-1}, n_{p-2}, \dots, n_0)} = \frac{1}{N} A_p(n_{p-1}, n_{p-2}, \dots, n_0) \quad (3.35)$$

Thus it is seen that the complete transform may be obtained in  $N \log_2 N$  addition and subtraction operations rather than  $N^2$  operations demanded by the direct method of calculation for equation (3.5).

A summary of the mathematical operations required in the evaluation of several orthogonal transformations is given in Table 3.4. These compare the number and type of operations needed to calculate the transform for the discrete and fast forms of the algorithm. A fast transform algorithm does not exist for the Karhunen–Loeve transform.

Transform	Mathematical operations
Discrete Fourier	$N^2$ complex multiply-additions
Fast Fourier	$N \log_2 N$ complex multiply-additions
Discrete Walsh	$N^2$ addition/subtractions
Fast Walsh	$N \log_2 N$ additions/subtractions
Discrete Haar	$N^2$ additions/subtractions
Fast Haar	$2(N - 1)$ additions/subtractions
Discrete Karhunen–Loeve	$N^2$ multiply-additions

TABLE 3.4. Summary of transformation operations.

### IIIH2 Signal flow diagrams

Computation for the fast transform algorithms can be described conveniently by means of the signal flow diagram. This consists of a series of nodes, each representing a variable which is itself expressed as the sum of other variables originating from the left of the diagram, with the nodes connected together by means of straight lines. The weighting of these

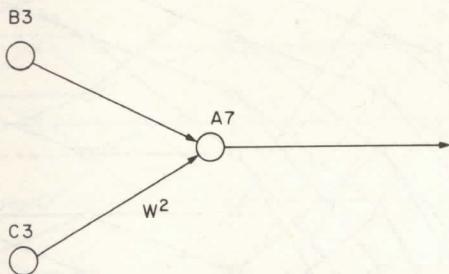


FIG. 3.2. A signal flow diagram.

itions is indicated by a number appearing at the side of an indicating  
ow shown on these connecting lines. Thus from Fig. 3.2, the variable  $A_7$   
erived from variables originating at nodes  $B_3$  and  $C_3$ , with the latter  
ghted by  $W^2$ , so that we can write

$$A_7 = B_3 + W^2 \cdot C_3 \quad (3.36)$$

Figure 3.3 shows a signal flow diagram for a sequency-ordered Walsh  
transform<sup>8</sup> which corresponds to the mathematical development given in  
Section IIIH1. The solid lines in the diagram indicate that the calculated  
value is to be carried forward to the addition at the next node with the same  
sign, and a dotted line indicates multiplication by  $-1$  before addition takes  
place.

### 3 "In-place" algorithms

The final calculation stage, illustrated in the signal flow diagram of Fig. 3.3, is  
interesting since it shows a series of identical self-contained operations  
carried out on two values only. This is reproduced in Fig. 3.4 and has been  
referred to as a "butterfly" diagram. Here the output value  $D_1$  is obtained  
from a linear combination of  $C_1$  and  $C_2$ , whilst  $D_2$  is obtained from the  
combination  $C_1$  and  $C_2$  with the latter modified by a sign inversion.

These butterflies have the inherent advantage that in each of the transformation steps once a pair of data locations have been read then they can be  
overwritten by the calculated pair of output values. This is the key to  
"in-place" algorithms in which memory storage for intermediate stage  
calculations is not needed since the calculated values can be placed back into  
memory locations occupied previously by the initial data values. A signal  
flow diagram for an "in-place" algorithm is shown in Fig. 3.5. This gives  
results in bit-reversed order so that an auxiliary sorting sequence is required  
to achieve binary reversal and hence linear sequency order. A study of the  
signal flow diagram will show that calculation can proceed as a series of simple  
"butterfly" calculations requiring no intermediate storage locations.

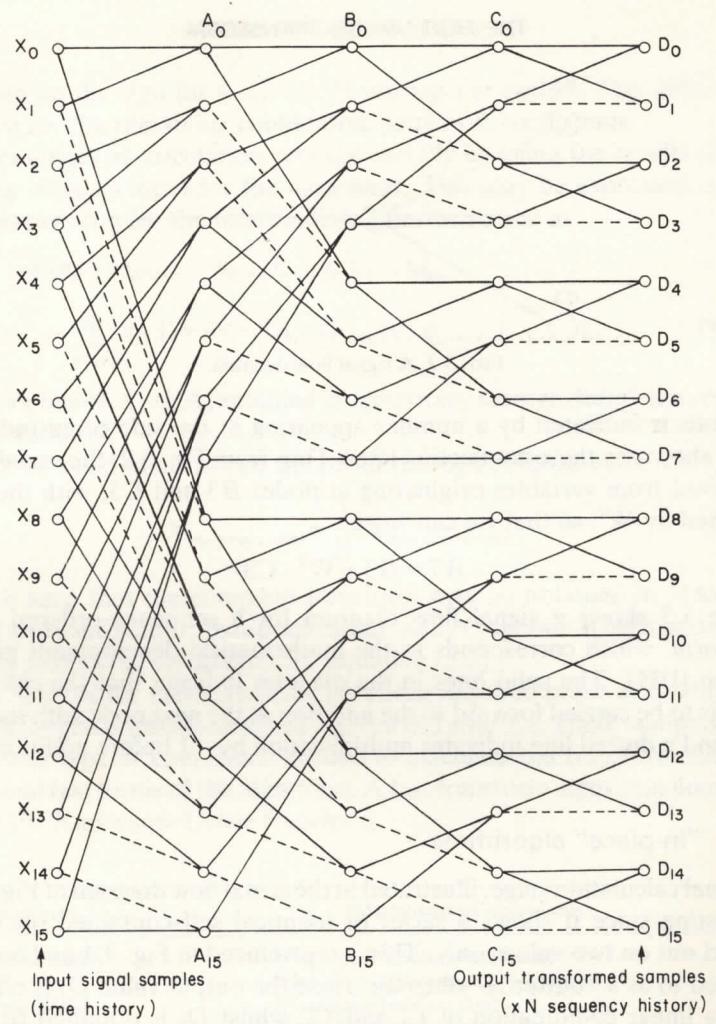


FIG. 3.3. A signal flow diagram for a sequency-ordered discrete Walsh transform (F.W.T.).

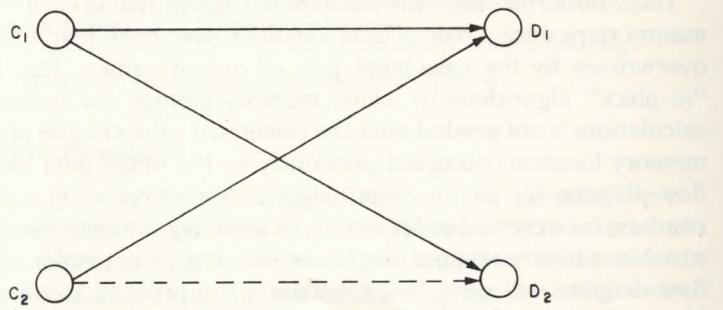


FIG. 3.4. A "Butterfly" of a signal flow diagram.

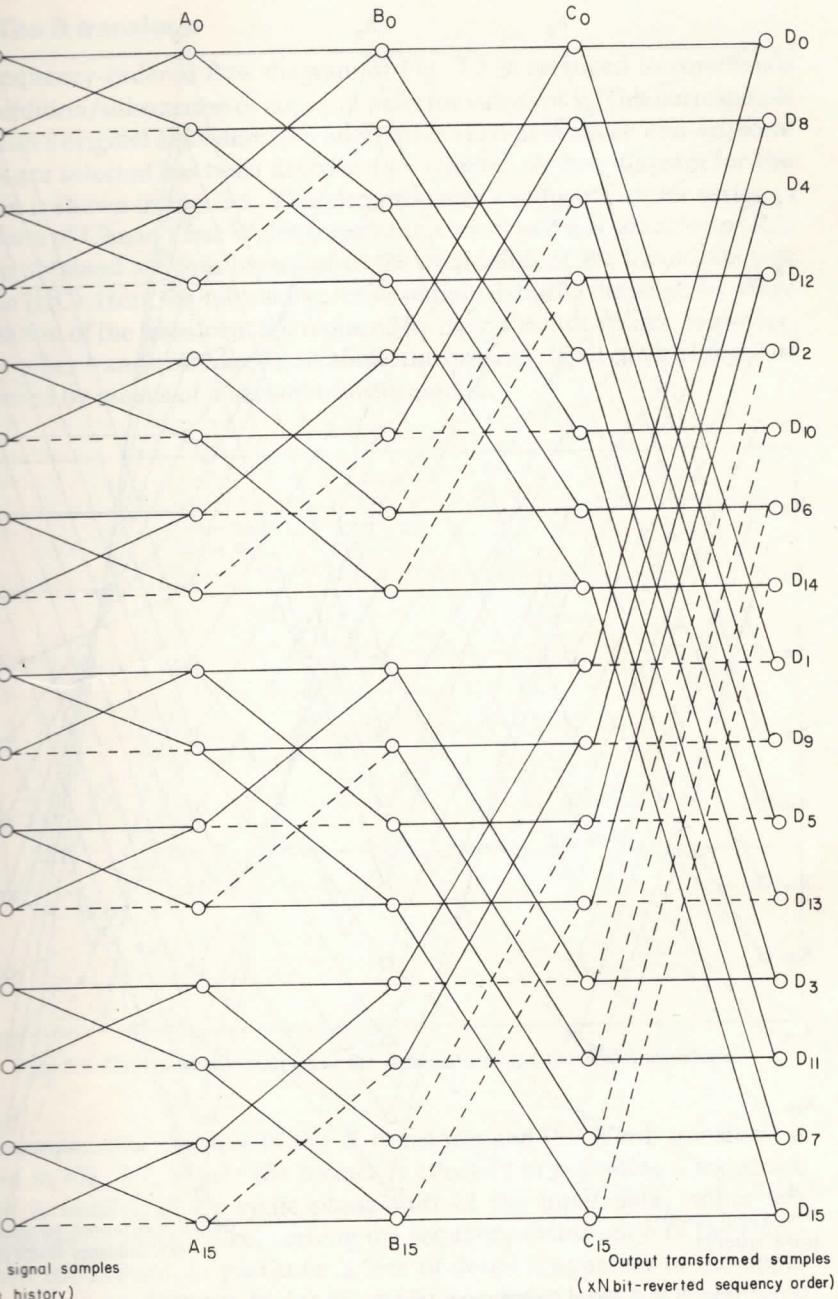


FIG. 3.5. A signal flow diagram for an "in-place" algorithm (F.F.W.T.).

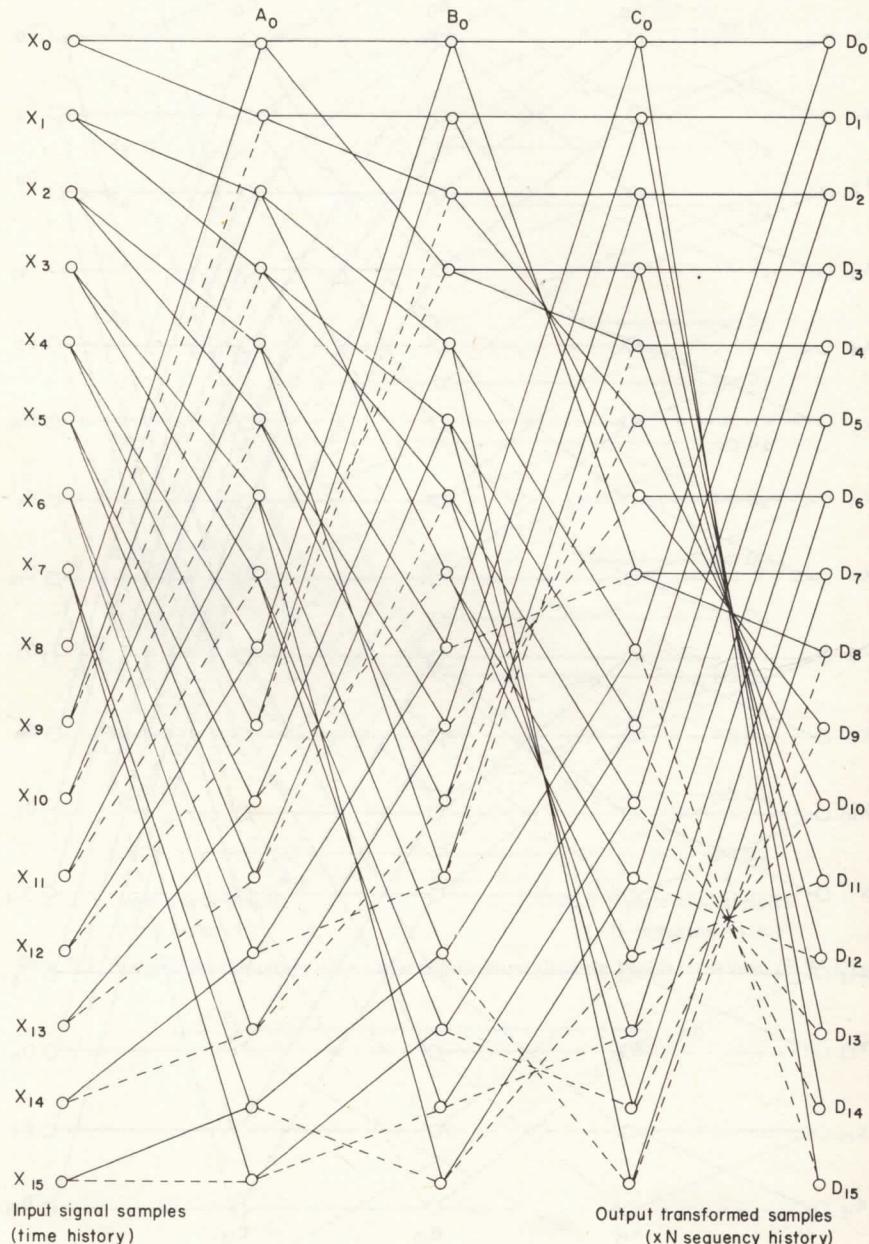


FIG. 3.6. A signal flow diagram for Ulman's algorithm (F.H.T.).  $N = 2^4$ .