Appendix A

Discrete Fourier Transform

The Discrete Fourier Transform (DFT) is a method for finding the frequency components of a signal. (It is named after Jean Baptiste Joseph Fourier, an early 19th century French mathematician.) The human ear does something very similar using the cochlea. The cochlea is a mechanical filter whereas the DFT is a mathematical filter. Both serve a similar purpose in speech recognition, that of transforming incoming sound into its frequency components.

Figure A.1 is a spreadsheet example of the DFT to extract the frequency components of a signal S(t). In effect, the sine and cosine of various frequencies are correlated against the signal S(t). Here we check only three frequencies since we know apriori the frequencies in S(t). Normally, for the 32 sample signal shown, 16 frequencies would be checked (16 sine and/or cosine values = 32 coefficients). These are $cos(n\omega t)$, n = 0,...,16, and $sin(n\omega t)$, n = 1,...,15. This insures that all of the energy in the time domain signal is accounted for in the frequency domain representation.

The important point to note here from the spreadsheet is that each frequency component may be found independently of the others. That is, the determination of the magnitude of $sin(n\omega t_j)$ or $cos(n\omega t_j)$ is found by calculating

$$A_{n} = \frac{\sum_{j=0}^{j=M-1} \cos(n \cdot \omega \cdot t_{j}) \cdot S(t_{j})}{\sum_{j=0}^{j=M-1} \cos^{2}(n \cdot \omega \cdot t_{j})} \quad \text{and} \quad B_{n} = \frac{\sum_{j=0}^{j=M-1} \sin(n \cdot \omega \cdot t_{j}) \cdot S(t_{j})}{\sum_{j=0}^{j=M-1} \sin^{2}(n \cdot \omega \cdot t_{j})} \quad (1)$$

where M = Number of Samples.

All this begs the question, how did this formula come about. Why would anyone think to multiply two sequences together (say $sin(n\omega t_j)$ and S(tj)) and then sum the individual products? The answer lies in the Method of Least Squares, one of the most powerful concepts in applied mathematics. It underlies Kalman filters, pattern recognition, machine learning, and, of course, regression analysis, among others. See the Wikipedia entry <u>http://en.wikipedia.org/wiki/Least_squares</u>.

The German mathematician Karl Friederich Gauss is credited with the discovery of the Method of Least Squares. Independently, the French mathematician Adrien-Marie Legendre discovered the method also. Much to the chagrin of Gauss, Legendre actually published before Gauss. This led to a feud between these two great mathematicians.

Briefly, the method finds the coefficients c_n in a mathematical model (e.g., $c_0 + c_1 \cdot x + c_2 \cdot x^2$) that minimizes the sum of the squares of the difference between a given data set (sequence of numbers) and the model. That is, for our simple polynomial example:

$$\sum_{j=0}^{j=M-1} \left(S_j - \left(c_0 + c_1 \cdot x_j + c_2 \cdot x_j^2 \right) \right)^2 = \text{minimum}$$
(2)

Using differential calculus (differentiating with respect to c_0 , c_1 , c_2 and setting each result equal to zero), it is straightforward to show that this minimization leads to three simultaneous linear equations in c_0 , c_1 , c_2 :

$$c_{0} \cdot \sum_{j=0}^{j=M-1} 1 + c_{1} \cdot \sum_{j=0}^{j=M-1} x_{j} \cdot 1 + c_{2} \cdot \sum_{j=0}^{j=M-1} x_{j}^{2} \cdot 1 = \sum_{j=0}^{j=M-1} S_{j} \cdot 1$$
(3a)

$$c_{0} \cdot \sum_{j=0}^{j=M-1} x_{j} + c_{1} \cdot \sum_{j=0}^{j=M-1} x_{j}^{2} + c_{2} \cdot \sum_{j=0}^{j=M-1} x_{j}^{3} = \sum_{j=0}^{j=M-1} S_{j} \cdot x_{j}$$
(3b)

$$c_{0} \cdot \sum_{j=0}^{j=M-1} x_{j}^{2} + c_{1} \cdot \sum_{j=0}^{j=M-1} x_{j}^{3} + c_{2} \cdot \sum_{j=0}^{j=M-1} x_{j}^{4} = \sum_{j=0}^{j=M-1} S_{j} \cdot x_{j}^{2}$$
(3c)

While there are many methods for solving simultaneous linear equations, if the mathematical model consists of sines and cosines whose frequency corresponds to integer multiple wavelengths of the sample segment interval (the DFT meets this requirement), then each equation reduces to:

$$A_{n} \cdot \sum_{j=0}^{j=M-1} \cos^{2}(n \cdot \omega \cdot t_{j}) = \sum_{j=0}^{j=M-1} \cos(n \cdot \omega \cdot t_{j}) \cdot S(t_{j})$$
(4a)

$$B_n \cdot \sum_{j=0}^{j=M-1} \sin^2(n \cdot \omega \cdot t_j) = \sum_{j=0}^{j=M-1} \sin(n \cdot \omega \cdot t_j) \cdot S(t_j)$$
(4b)

which may be readily solved for A_n and B_n , as shown on the previous page.

If all of this just seems like so many Greek characters, the spreadsheet of Figure A.1 is an illustration of this process. Column A is the time in milliseconds, column B is the angle ωt_j . The angular frequency ω is chosen such that $\omega \Delta T = 2\pi$. ΔT is the sample segment interval.

Columns C through H are the numerical values of the sines and cosines of $n\omega t_j$, n = 1, 2, 3 at the times $t_j = 0, 1, ..., 31$. Similarly, column I contains the numerical values of the assumed signal

$$S(t_j) = 2*Sin(\omega t_j) - 3*Cos(2\omega t_j) + 1*Sin(3\omega t_j).$$

If we sum the products of any two pair of columns C through I, we obtained the $6 \ge 7$ array at the bottom of the page. The left $6 \ge 6$ array confirms that the sum of products of columns C through H that

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are paired with themselves are non-zero. This is another way of illustrating the orthogonality of the sine and cosine functions in the interval ΔT with $\omega = 2\pi / \Delta T$. The summations on the left side of equations (4a) and (4b) are the non-zero result (= M/2 = 16 in the spreadsheet).

The seventh column is the sum of the products of columns C through H paired with column I. This is the right side of equations (4a) and (4b).

Thus, to find the A_n and B_n , we need only divide the results in the last column by the non-zero result in the same row of the 6 x 6 array. Thus,

$$B1 = 32/16 = 2$$
, $A1 = 0$, $B2 = 0$, $A2 = -48/16 = -3$, $B3 = 16/16 = 1$, and $A3 = 0$.

The coefficients recovered are identical to the coefficients in our assumed signal S(t). The lower right corner spreadsheet calculation obtains the same result.

Interestingly, if we calculate the power in S(t) and in the frequency components, we find they are equal.

First, the frequency components:

$$P(A_n, B_n) = \frac{1}{2} \sum_{n=1}^{3} (A_n^2 + B_n^2)$$
$$= \{2^2 + (-3)^2 + 1^2\}/2 = 7$$

The factor 1/2 is required because the components are peak values, not RMS.

The power in the signal $S(t_j)$ is:

$$P(S(t)) = \frac{1}{M} \sum_{j=0}^{j=M-1} S(t_j)^2 = 7$$
 (From the spreadsheet)

This is calculation is from the spreadsheet. The fact that $P(A_n, B_n) = P(S(t))$ is known as Parcival's Theorem. In effect, no energy is lost or gained transforming from the time domain to the frequency domain.

As a final comment, the Fast Fourier Transform produces the same result, but takes advantage of certain redundancies in the calculation if M is a power of 2, e.g. 2, 4, 8, 16, 32, 64, etc. See the Wikipedia entry <u>http://en.wikipedia.org/wiki/Fast_Fourier_transform</u>.

The functioning spreadsheet may be found on the CD-ROM.

A Simple Non-Rigorous Example of Frequency Component Determination

	π =	3.14152		Samples =	32		S(t) = 2*Sin(ωt) - 3*Cos(2	$2\omega t$) + Sin($3\omega t$)
	$\omega = 2^*\pi / \Delta T =$	0.19635		$\Delta T =$	32		\	V	/
А	В	С	D	E	F	G	Н	I	
t	ωt	Sin(ot)	Cos(wt)	Sin(2ct)	Cos(2wt)	Sin(3œt)	Cos(3wt)	S(t)	
0	0	0	1	ò	1	ò	1	-3	1.5
1	0.2	0.2	0.98	0.38	0.92	0.56	0.83	-1.83	
2	0.39	0.38	0.92	0.71	0.71	0.92	0.38	-0.43	0.5
3	0.59	0.56	0.83	0.92	0.38	0.98	-0.2	0.94	-0.5
4	0.79	0.71	0.71	1	0	0.71	-0.71	2.12	-1
5	0.98	0.83	0.56	0.92	-0.38	0.2	-0.98	3.01	-1.5
6	1.18	0.92	0.38	0.71	-0.71	-0.38	-0.92	3.59	
7	1.37	0.98	0.2	0.38	-0.92	-0.83	-0.56	3.9	1.5
8	1.57	1	0	0	-1	-1	0	4	
9	1.77	0.98	-0.2	-0.38	-0.92	-0.83	0.56	3.9	
10	1.96	0.92	-0.38	-0.71	-0.71	-0.38	0.92	3.59	
11	2.16	0.83	-0.56	-0.92	-0.38	0.19	0.98	3.01	
12	2.36	0.71	-0.71	-1	0	0.71	0.71	2.12	
13	2.55	0.56	-0.83	-0.92	0.38	0.98	0.2	0.94	-1
14	2.75	0.38	-0.92	-0.71	0.71	0.92	-0.38	-0.43	-1.5
15	2.95	0.2	-0.98	-0.38	0.92	0.56	-0.83	-1.83	
16	3.14	0	-1	0	1	0	-1	-3	1.5
17	3.34	-0.2	-0.98	0.38	0.92	-0.56	-0.83	-3.72	
18	3.53	-0.38	-0.92	0.71	0.71	-0.92	-0.38	-3.81	
19	3.73	-0.56	-0.83	0.92	0.38	-0.98	0.19	-3.24	-0.5
20	3.93	-0.71	-0.71	1	0	-0.71	0.71	-2.12	
21	4.12	-0.83	-0.56	0.92	-0.38	-0.2	0.98	-0.71	-1.5
22	4.32	-0.92	-0.38	0.71	-0.71	0.38	0.92	0.66	
23	4.52	-0.98	-0.2	0.38	-0.92	0.83	0.56	1.64	6
24	4.71	-1	0	0	-1	1	0	2	4
25	4.91	-0.98	0.19	-0.38	-0.92	0.83	-0.56	1.64	2
26	5.1	-0.92	0.38	-0.71	-0.71	0.38	-0.92	0.66	
27	5.3	-0.83	0.56	-0.92	-0.38	-0.19	-0.98	-0.71	
28	5.5	-0.71	0.71	-1	0	-0.71	-0.71	-2.12	
29	5.69	-0.56	0.83	-0.92	0.38	-0.98	-0.2	-3.24	-4
30	5.89	-0.38	0.92	-0.71	0.71	-0.92	0.38	-3.81	-6
31	0.09	-0.2	0.96	-0.36	0.92	-0.56	0.65	-3.72	
		Sin(œt)	Cos(ωt)	Sin(2ωt)	Cos(2wt)	Sin(3œt)	Cos(3ωt)	S(t)	The matrix at left implies: $\Sigma[Sin(not)*Sin(mot)] = 16$, if $m = n$, = 0 otherwise (for this example) $\Sigma[Cos(not)*Cos(mot)] = 16$, if $m = n$, = 0 otherwise
	Sin(ωt)	16	0	0	0	0	0	32	$\Sigma[Sin(not)*Cos(mot)] = 0, all m, n$ The choice preparty of the close and excises is extracted by We may use this preparty for
	Cos(ωt)	0	16	0	0	0	0	0	easily find the frequency components of a signal.
	Sin(2wt)	0	0	16	0	0	0	0	If S(t) = 2*Sin(wt) - 3*Cos(2wt) + 1*Sin(3wt) (See Column I,S(t)), then computing
	0(0-*)	0	0	0	10	0	0	40	Σ [Sin(not)*S(t)] / Σ [Sin(not)*Sin(not)] and Σ [Sin(not)*Sin(not)]
	Cos(2@t)	U	U	U	10	U	U	-48	∠ເບວs(n∞t)*S(t)] / ∠[ບວs(n∞t)*ບວs(n∞t)]
	Sin(3ωt)	0	0	0	0	16	0	16	for S(t) and $n = 1, 2, 3$, (using the precomputed values from the array at left), yields the following:
	Cos(3wt)	0	0	0	0	0	16	0	Sin(wt) Cos(wt) Sin(2wt) Cos(2wt) Sin(3wt) Cos(3wt)
	Abo	ove entries are	the sum of pro	ducts of the rov	v and column f	unctions, e.g.	, Σ [Cos(2ωt)*Sir	n(3∞t)].	2 0 0 -3 1 0

Parcival's Theorem: Power in signal $S(t) = \{\Sigma S(tj)2\} / Samples =$

= Power in frequency components = {22 + (-3)2 + 12}

-Column C

-Column D

-Column E

Column F

-Column G

-Column H

Column I

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