A STUDY OF THE CONTRIBUTION OF THE FIRST AND SECOND HEART SOUNDS AT FREQUENCIES GREATER THAN 100 Hz TO RESPIRATORY SOUND DATA RECORDED AT THE TRACHEA

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ABSTRACT

One of the problems associated with the quantitative analysis of respiratory sound data has been interference due to the presence of heart sounds. In the past, heart sounds have typically been filtered using cutoff frequencies of less than 75 Hz. This study investigates the possibility of significant heart sound contribution to respiratory sound data recorded at the trachea at frequencies greater than 100 Hz. Segments of breaths from ten subjects with and without heart sounds were analyzed and then compared using a paired difference (or paired population) t test. The data was filtered using a 100 Hz, 8 pole digital filter prior to analysis. The results show that the presence of heart sounds does significantly affect respiratory sound data as described by a set of twenty-five parameters.

ACKNOWLEDGEMENTS

I would like to express my thanks to Dr. Charles Lessard for his support, patience, and advice. By allowing me a free reign, he has helped to make this an important learning experience and a rewarding one.

I would also like to extend my thanks to Steve Mesibov, a graduate student in bioengineering. He developed all the hardware and software used during this study and was the driving force behind what is presented here. This study is part of a larger project investigating the use of respiratory sound as a diagnostic tool, of which Steve is the project leader, working under Dr. Lessard.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

A STUDY OF THE CONTRIBUTION OF THE FIRST AND SECOND HEART SOUNDS AT FREQUENCIES GREATER THAN 100 Hz TO RESPIRATORY SOUND DATA RECORDED AT THE TRACHEA

INTRODUCTION

The existence of a relationship between respiratory sounds and gross respiratory condition has been known for hundreds of years. In the early 1800's, Laennec invented the stethoscope in order to facilitate the collection of respiratory sound data and to better explore the relationship between sound and gross pathology. Although many modifications have since been made, this same basic system is still the one most widely used today to assess the condition of the lower respiratory tract. In the hands of a "trained observer" (typically a physician), the stethoscope can be a very powerful diagnostic tool. It does, however, necessitate a subjective interpretation of the data collected. As a result, there are varying degrees of acceptance of respiratory sounds as a clinical sign. Furthermore, this system is limited by the responsiveness of the stethoscope and the sensitivity of the human ear.

There has, therefore, been an interest in the past twenty years in developing a quantitative means of assessing the condition of the respiratory tract by analyzing respiratory sounds. One problem that has been encountered when conducting this kind of research is the

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presence of heart sounds. The sounds produced by the heart valves as the atria and ventricles contract are picked up with great intensity at both the chest wall and the trachea. These sounds are usually categorized as the first through fourth heart sounds. The first two sounds correspond to the QRS and T waves of the EKG, respectively. They are the heart sounds of interest in this study as the third and fourth sounds are of very small intensity in normal individuals. The first heart sound has been shown to have a peak at about 30 Hz in normal individuals, followed by a steady decline in intensity (-18 dB/octave).[1] In contrast, the second heart sound shows no consistent peak, but rolls off as a function of frequency more gradually.[2] The first heart sound is 40 dB down from its 10 Hz value at 100 Hz whereas the second heart sound is only about 30 dB down. The tendency in past studies investigating respiratory sound as a clinical indicator has been to use a high pass filter (a filter which discriminates against sounds below a certain frequency) to remove the relatively low frequency heart sounds. These filters have typically been set to begin filtering at frequencies less than 75 Hz (see reference 3, for example), frequencies considered too low to be of interest in respiratory sound analysis. There is some evidence to indicate, however, that heart sounds contribute significant amounts of energy at frequencies much higher than originally speculated. This study, then, will investigate the possibility that the first and second heart sounds do indeed significantly contribute to the power spectrums of respiratory sounds as recorded at the trachea at frequencies greater than 100 Hz.

METHODS AND MATERIALS

Data Collection: The ten subjects used in this investigation were all males between the ages of twenty-one and twenty-five. None had evidence of significant respiratory or heart pathology and, in addition, none were smokers (see Appendix I).

An Archer (270-092 B) electret condenser mike element was used to pick up sound at the trachea. The manufacturer's specifications showed it to have a flat response from 20 Hz to 10,000 Hz (± 5 dB). The microphone was supported in a hollow, wooden dowel of outer diameter 1.3 cm (see Figure 1). The face of the microphone was flush with the edge of the dowel. This dowel was then epoxied inside a second wooden dowel with a tapered nose. The microphone was 0.3 cm from the mouth of the second dowel. The second dowel was held against the trachea by an elastic strap that encircled the patient's neck. The patient was seated comfortably and asked to breathe normally, with the mouth slightly open. A Lafayette Instruments pneumograph was strapped around the patient's chest. It is sensitive to changes in the diameter of the chest, and as such, was used to determine inspirations and expirations.

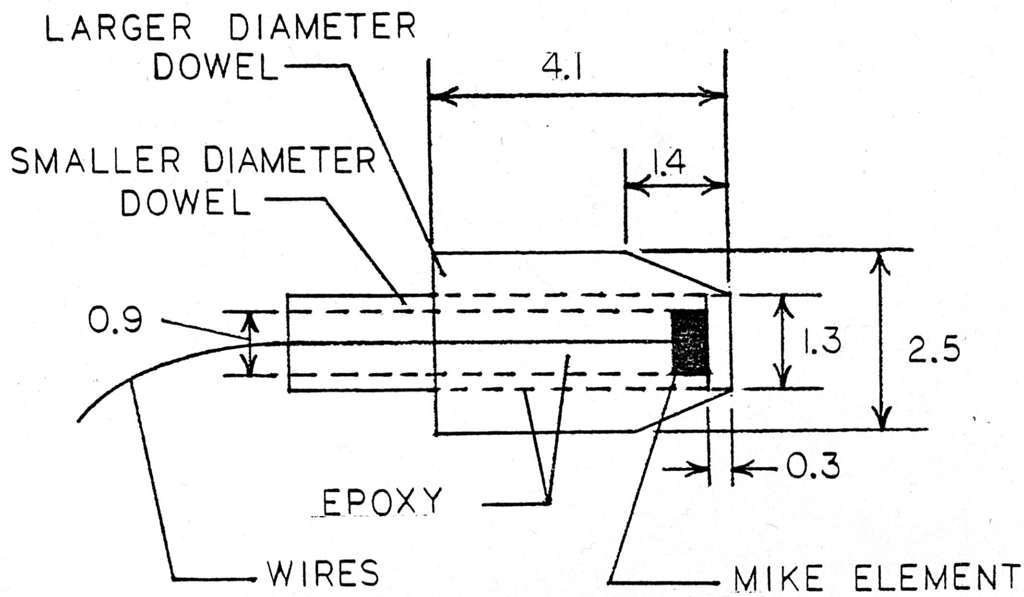

Figure 1. Schematic of nose cone with mike element used to record sound data at the trachea. (All lengths are in cm.)

Figure 2 shows a block diagram of the system used to collect data. The microphone signal was amplified 10X, and then filtered so as to achieve a heart sound amplitude that was approximately the same as the peak respiratory sound amplitude. The filters used were either a high pass 50 Hz-5 pole, 75 Hz-2 pole, 100 Hz-5 pole, or combination of the above. Since no sounds of less than 100 Hz frequency were of interest in this study, we did not feel it necessary to keep the filtering constant across the ten subjects. Filtering was kept constant within each subject. The filtered signal was amplified again from 0-50X, and both the microphone and pneumograph signal were recorded on Scotch Metafine metal cassette tape using a Harman/Karden linear phase cassette deck recorder. Both signals were viewed on a Tektronix 511A oscilloscope.

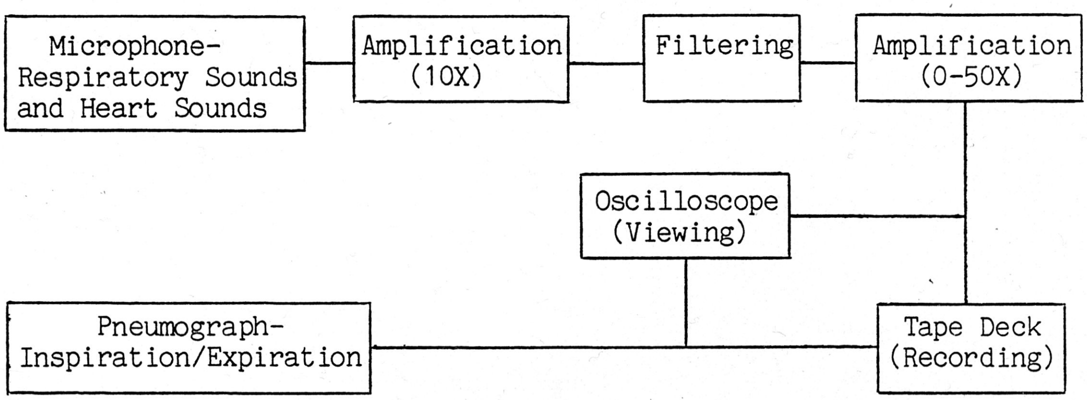

Figure 2. Diagram of process of data collection.

<u>The Fast Fourier Transform</u>: Throughout this study, data is initially recorded as a function of time. In addition, the original signal is a continuous one. Figure 3, for example, is a plot of the intensity of sound (in volts) recorded at the trachea for one inspiration as a function of time. When analyzing the data, it is not desirable to have it displayed in the time domain. The reason for this is that very little information useful in discriminatory analysis can be obtained from such data. Instead, it is desirable to have the data represented as a function of frequency. Moreover, in order to use a digital computer

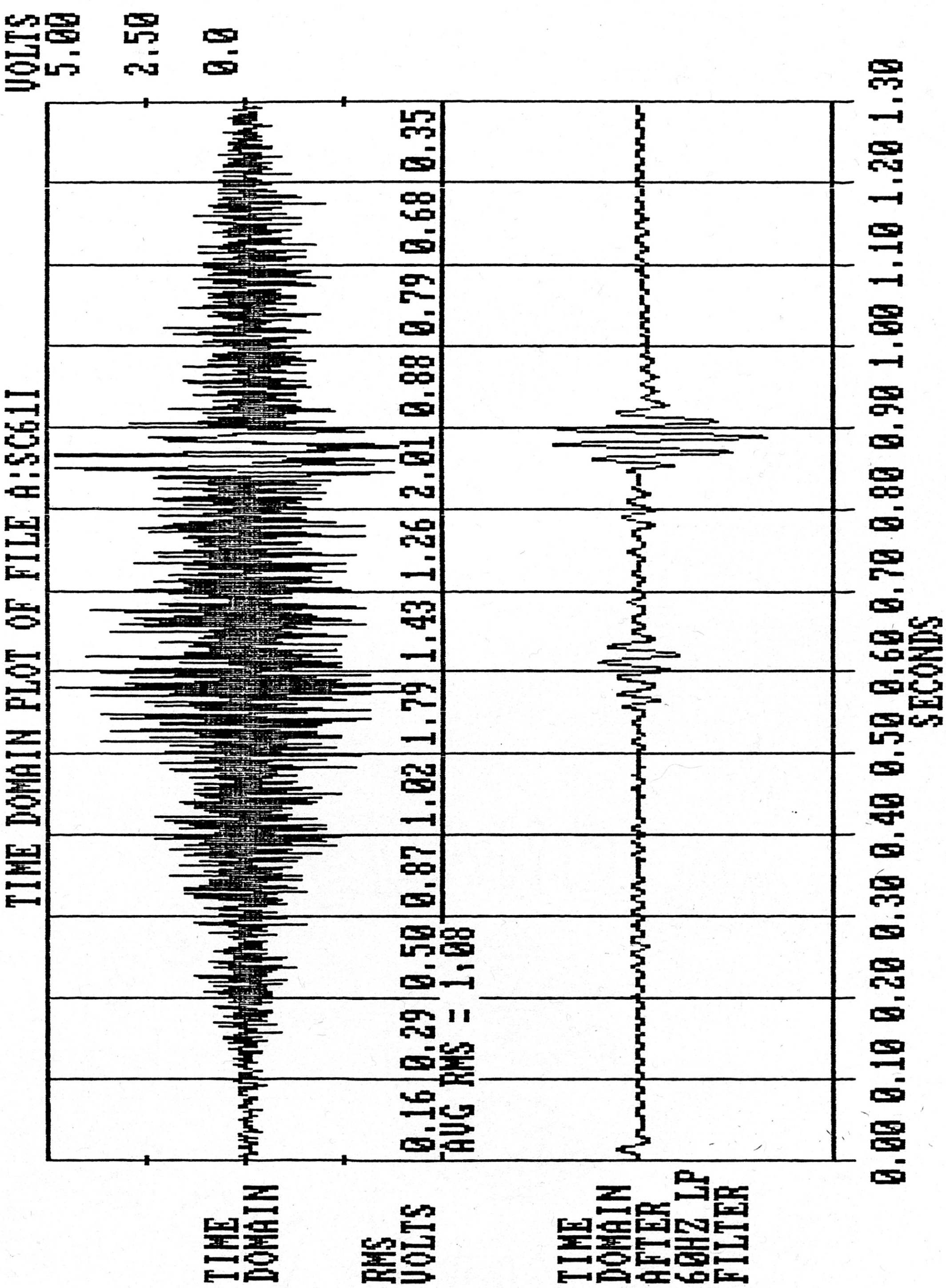

Figure 3. Time domain plot of typical breath.

to carry out the analysis, the data must be digitized. This means that it must be presented to the computer as discrete pieces of information and not as a continuous stream. From data in the frequency domain, differences in the distribution of the energy in a breath as a function of frequency can be determined. The parameters used to describe the data in this study (see Appendix II for a complete listing) are all means of trying to uncover these differences.

The mathematical tool that is used to convert a time-domain signal into a signal in the frequency domain is the Fourier transform. For continuous signals, the transform pair can be written as:

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-iwt}dt \qquad (1)$$

$$\text{and } x(t) = \int_{-\infty}^{\infty} X(f)e^{iwt}df \qquad (2)$$

where $-\infty<f<\infty$, $-\infty<t<\infty$, and $i=\sqrt{-1}$. In these equations, $X(f)$ represents the frequency-domain function whereas $x(t)$ represents the same function in the time domain. The Fourier transform is derived from the Fourier series. The idea of the Fourier series is to represent a function by an infinite series of sinusoids of harmonically related frequencies. A derivation of the transform equations above from the equations for the Fourier series can be found in reference 4.

As already discussed, the digital computer can only accept finite, discrete quantities of information. Therefore, equations 1 and 2 must be modified in order to accommodate a system that is taking samples of a continuous signal at regular intervals and using these as an approximation of that signal. These modified transform equations are referred to as the discrete Fourier transform pair and can be written as:

$$X(j) = \frac{1}{N} \sum_{k=0}^{N-1} x(k) e^{-i2\pi jk/N} \tag{3}$$

$$\text{and } x(k) = \sum_{j=0}^{N-1} X(j) e^{i2\pi jk/N} \tag{4}$$

where j=0, 1, . . ., N-1 and k=0, 1, . . ., N-1. A derivation of the equation for the discrete Fourier transform from the continuous Fourier transform can be found in references 5 and 6.

The fast Fourier transform (FFT) is simply a rapid, efficient method for computing the discrete Fourier transform.[7]

Data Sampling: Data sampling is the name given to the process of selecting discrete points of data from a continuous signal. These discrete points are then used as an approximation of the original signal. The fast Fourier transform algorithm used in this study has a sampling rate of 2083 data points/second. If, in addition, a 512 point FFT is used, then the resolution of the sampled signal is 2083/512 or approximately 4 Hz. These numbers remained fixed throughout this study.

For this study, only <u>segments</u> of appropriate breaths were analyzed. Using only finite segments of a continuous signal is equivalent to multiplying that signal by a rectangular window function. This window function (analogous to an ON/OFF switch) tells the computer when to sample the signal. Unfortunately, using a rectangular window function introduces certain problems. At the boundaries of the function, where the window is being "opened" and "closed," a kind of error referred to as leakage occurs. The error is a result of the FFT's inability to represent the discontinuities seen at the rising and falling edges of the window. This error can be minimized by tapering the edges of the window so that there are no discontinuities. The taper used in this study to minimize leakage is a ten percent cosine taper. Using this taper, the first data point is forced to zero and the rising edge of the window is a cosine function. The equations for the ten percent cosine taper are:

$$\begin{aligned} &0.5(1 - \cos(10\pi \times I/N)) && \text{for } 0<I<N/10 \\ &1 && \text{for } N/10<I<N \times 9/10 \qquad (5) \\ \text{and } &0.5(1 - \cos(10\pi \times I/N)) && \text{for } N \times 9/10<I<N \end{aligned}$$

where N is the number of data points sampled for the FFT calculation.[4] N = 824 data points throughout this study.

The Power Spectrum: Once the data is transformed into the frequency domain, it is plotted as power vs. frequency. This kind of plot is commonly referred to as a power spectrum. An example of the power spectrum for a typical inspiration is shown in Figure 4. Recall that the Fourier series attempts to describe a function as an infinite series of sinusoids:

$$f(t) = \frac{a_0}{2} + \sum_{n=1}^{\infty} (a_n \cos nw_0 t + b_n \sin nw_0 t). \qquad (6)$$

The Fourier series can also be expressed in an exponential form:

$$f(t) = \sum_{n=-\infty}^{\infty} c_n e^{inw_0 t}. \qquad (7)$$

(Reference 8 has a derivation of the exponential form from the trigonometric form.) If a_i represents the real component of the ith Fourier series coefficient and b_i represents the imaginary component, then the complex coefficient c_i can be calculated as:

$$c_i = \sqrt{a_i^2 + b_i^2} \qquad (8)$$

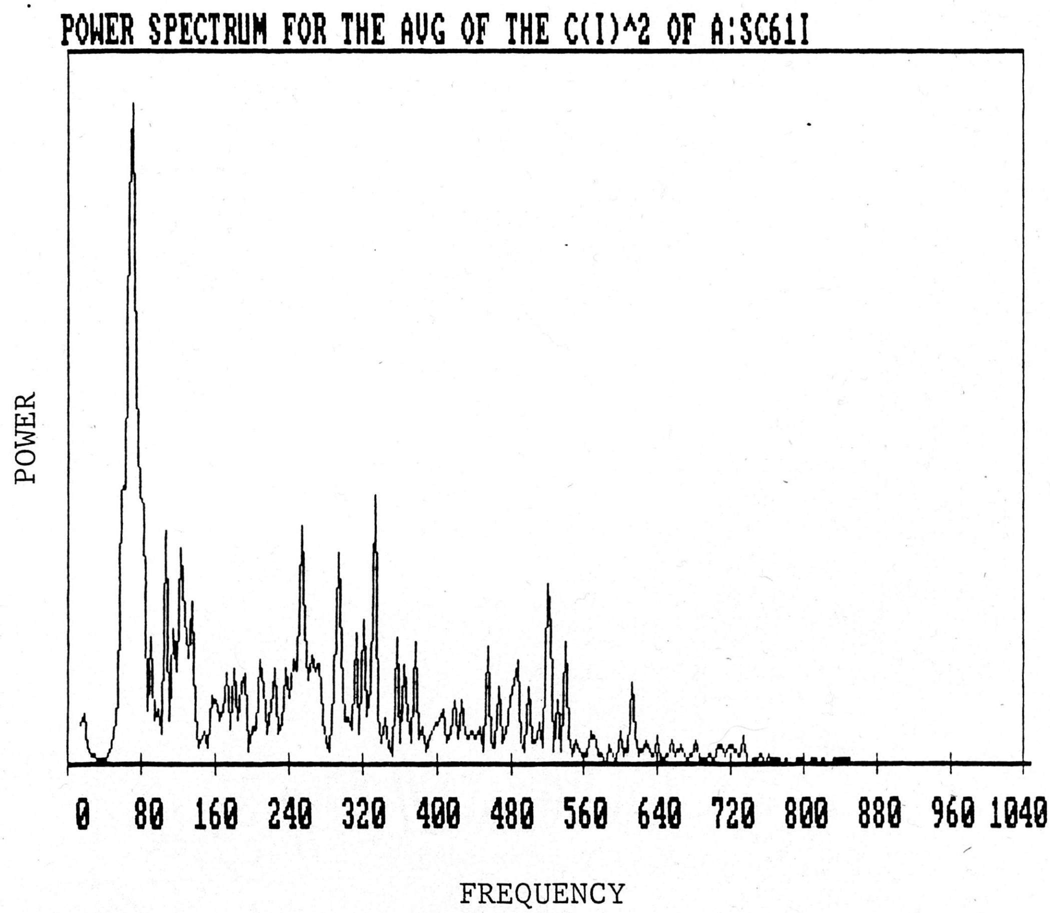

Figure 4. Power spectrum (frequency domain plot) for a typical breath. The peak centered at 75 Hz is due to heart sounds. It will be filtered out during analysis. The peaks between 80 Hz and 150 Hz could be from either heart or respiratory sounds. All peaks occurring at frequencies greater than 240 Hz are almost certainly due to breath sounds. Note the relative intensity of the 75 Hz peak compared to the rest of the spectrum. Also observe that there is no significant contribution to the spectrum above about 850 Hz.

where a_i, b_i, and c_i all have the units of volts. Power is calculated as V^2/R, where V is voltage and R stands for resistance. Thus, by squaring c_i and assuming the resistance to be 1 ohm, the units for power are achieved. A power spectrum, then, is a plot of the squares of the complex coefficients of the Fourier series as a function of frequency. The complex coefficients are computed from the fast Fourier transform.[4,8]

Data Analysis: An outline of the main steps in the data analysis process is shown in Figure 5. The raw data for each subject was reviewed and breaths selected for future analysis. A 900 Hz low-pass filter was employed to protect against aliasing. These breaths were digitized using an ISAAC 2000 A/D converter and stored on an IBM PCXT hard disk. The digitization and storage were triggered using the chest expansion data from the pneumograph.

This refined data was further reviewed so that segments of breaths on which analysis would be performed could be chosen. Two general occurrences were searched for: breath segments in which the first and second heart sounds were included and segments not containing these sounds. For example, the breath in Figure 3 would be used for combined heart and respiratory sounds. The bottom plot (60 Hz low-pass filter) better shows exactly where in the breath the first and second heart sounds occur. A

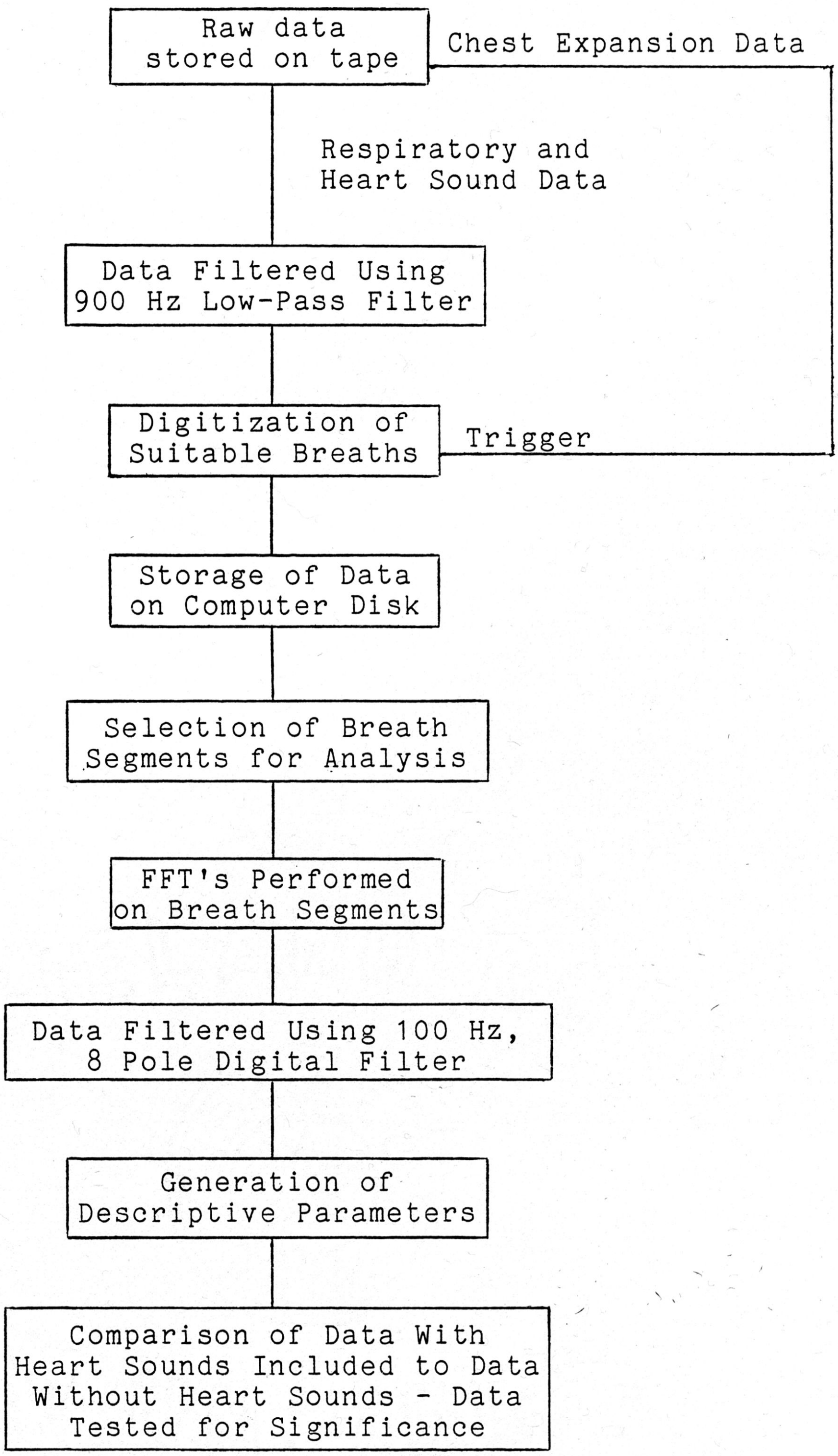

Figure 5. Diagram of steps in data analysis.

breath segment beginning at about 0.55 s and extending to 0.95 s would include both heart sounds. In addition, as a result of studies done by Charbonneau[3], Wong[9], and others, which demonstrated differences in the parameters used to describe respiratory sound data depending on whether the subject was inhaling or exhaling, inspirations were treated separately from expirations on all occasions.

The segments of breaths selected were 824 data points long or approximately 0.4 s in length (sampling rate = 2083 data points/second). For data containing heart sounds, this was just long enough to include both the sounds. The position in the breaths that the segments of data were taken from was not strictly controlled for; however, the very beginnings and ends of breaths were excluded from consideration. Segments representing five inspirations without heart sounds, five inspirations with heart sounds, five expirations without heart sounds, and five expirations with heart sounds were obtained for each subject.

The next step in the data analysis sequence was to transform the breath segments isolated above from the time domain into the frequency domain. Four 512 point FFT's were performed on each breath segment, with ~0.05 increments between each FFT, and then averaged together. The result, as was shown in Figure 4, is a plot of power (averaged for the 4 FFT's) vs. frequency for each breath segment. This "frequency-domain data" was then stored on hard disk. Each breath segment so stored was then analyzed using a parameter generating program that produced twenty-five descriptive parameters. Immediately prior to the calculation of parameters, the data was filtered digitally using a 100 Hz-8 pole, high-pass filter.

For each subject, the parameters generated for all inspirations without heart sounds were averaged together, and the means and variances calculated. The same was done for inspirations with heart sounds and expirations with and without heart sounds. Inspirations with and without heart sounds and expirations with and without heart sounds for each subject were then compared using a Student t test with 8 degrees of freedom. This provides a parameter by parameter indication of the significance of heart sound interference in respiratory sound analysis. Finally, the data for all ten subjects was compared using a paired difference t test.

<u>The Student t Test</u>: The Student t test is a test commonly used to compare the means of small populations of data. More precisely, it can be used to determine whether two means are significantly different, given the distribution of the individual points of data around those means. When using the Student t test, the hypothesis that the two

sample means ($\overline{X}_1$ and $\overline{X}_2$) are not significantly different is adopted. A number referred to as the test statistic is then generated according to the formula given below:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{s_{pooled}\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \qquad (9)$$

where degrees of freedom = $n_1 + n_2 - 2$. This number is compared to a table of numbers compiled for the same sample size. An attempt is made to determine whether at some given high probability the hypothesis that $\overline{X}_1 = \overline{X}_2$ can be rejected.

Much of what was presented above requires further elaboration. $\overline{X}_1$ and $\overline{X}_2$ are the sample means. For this study, $\overline{X}_1$ is the mean of the data for the five inspirations or five expirations without heart sounds. Using data from Table I (see Results and Discussion section) as an example, $\overline{X}_1$ would be 414.8 Hz, 240.4 Hz, and 451.8 Hz in turn. $\overline{X}_2$, then, is the mean of the data for the five inspirations or five expirations that do include heart sounds. n_1 and n_2 refer to the sample sizes used. In every case, segments of 5 breaths were analyzed and averaged together. Therefore, $n_1 = n_2 = 5$ throughout this study. The pooled standard deviation, s_{pooled}, is an estimate of how widely scattered the individual data points are around their respective means. As one would expect, the more widely scattered the data is, the more difficult it is to show that the difference observed between the values of the two means is not the result of chance. The standard deviation is the square root of the variance (s^2_{pooled}). The pooled variance can be calculated from

$$s^2_{pooled} = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2} \qquad (10)$$

where s_1^2 is the variance of the data corresponding to $\bar{X}_1$ and s_2^2 is the variance of the data corresponding to $\bar{X}_2$. The individual variances are computed from the following equations:

$$s_1^2 = \frac{\sum_{i=1}^{n_1} (X_{1,i} - \bar{X}_1)^2}{n_1 - 1} \qquad (11)$$

$$\text{and } s_2^2 = \frac{\sum_{i=1}^{n_2} (X_{2,i} - \bar{X}_2)^2}{n_2 - 1} . \qquad (12)$$

The number of degrees of freedom of a sample population is a measure of how many unrelated deviations from the mean are found in that population. This number is a function of sample size. The degrees of freedom associated with a test statistic are used when trying to establish whether two means are significantly different. It should be obvious that as sample size increases, it becomes easier to prove that the difference observed in the values of two means is not the result of chance. This is reflected by the fact that the numbers in the t tables get smaller as degrees of freedom increase. In this study, since $n_1 = n_2 = 5$, the test statistic t has 8 degrees of freedom.

When using a Student t test, either a one-sided or two-sided test can be used. A one-sided test is used when it is known that $\overline{X}_1$ can only deviate significantly from $\overline{X}_2$ in one direction (i.e. $\overline{X}_1 \leq \overline{X}_2$ or $\overline{X}_1 \geq \overline{X}_2$). For example, common sense tells us that the mean power frequency (MPF), a measure of the central tendency of the distribution of data in the frequency domain, can only be reasonably expected to decrease by including the relatively low frequency heart sounds in the analysis. Therefore, a one-sided test can be used to compare the mean MPF's for data with and without heart sounds. If the relationship between $\overline{X}_1$ and $\overline{X}_2$ cannot be predicted as above, the more general two-sided test must be used. For example, it is difficult to say whether the variance of data with respect to the MPF (designated as VM) will be greater or lesser when heart sounds are included; thus, a two-sided test would be used to compare the mean VM's.

The results of t tests are usually expressed either in terms of confidence levels or levels of significance. Both are used to express how certain an investigator is that the results obtained were not due to chance but were, in fact, due to actual differences in the data. The letter α is used to designate the level at which the test statistic was tested against the table values. For example, if $\alpha = 0.05$, then the data was tested at a .05 level of significance. This corresponds to a .95 confidence level, which is calculated as $1 - \alpha$. If two means $\overline{X}_1$ and $\overline{X}_2$ are shown to be significantly different at $\alpha = 0.05$, the .95 confidence level this implies can be interpreted to mean that in 95% of the cases where $\overline{X}_1$ and $\overline{X}_2$ are as given, the difference observed is actually due to differences in the data and not to chance. Standard values for α are 0.01, 0.05, and 0.025.[10]

The Paired Difference t Test: This test is similar to the Student t test discussed above, with one primary exception. The paired difference t test compares the differences (D_i) between two series of means $\overline{X}_{1,i}$ and $\overline{X}_{2,i}$. It will be used to compare the results of all ten subjects combined. As an example, the mean MPF for subject #1's inspirations with heart sounds is subtracted from the mean MPF for his inspirations without heart sounds. The same is done for subjects two through ten. These ten differences are then averaged and tested to see whether, given the subject size, the average difference is significantly different from zero. This can be written as:

$$t = \frac{\overline{D} - \delta_0}{s_D/\sqrt{n}} \text{, degrees of freedom} = n-1, \qquad (13)$$

where $\overline{D}$ is the average (or mean) difference, $\delta_0 = 0$, n is subject size, and s_D is the standard deviation. The subject size will always be ten in this study. The square of the standard deviation, the variance, is given by:

$$s_D^2 = \frac{\sum_{i=1}^{n} (D_i - \overline{D})^2}{n - 1} \qquad (14)$$

Table III (see Results and Discussion section) was calculated using a paired difference t test.

The advantage of using the paired difference t test is that it eliminates the problem caused by the wide variations observed in mean parameter values from subject to subject. The discrepancies seen between subjects are probably due to a variety of factors, ranging from physiological differences to microphone placement to the patients' flow rates past the point of recording. If mean parameter values were averaged and compared, the result would be extremely large variances and standard deviations. This might lead to erroneously insignificant findings. The paired difference t test, by only comparing differences in data between subjects, provides a truer assessment of the contribution of heart sounds.[10]

RESULTS AND DISCUSSION

The mean parameter values, standard deviations, and results of the Student t tests for subject #1 are shown in Table I (see Appendix II for definitions of each of the parameters). Note that expirations and inspirations were tested separately. For a two-sided Student t test with 8 degrees of freedom, t must be greater than or equal to 2.306 to indicate significance at the .05 level. Certain parameters only require a one-sided test. These parameters include the mean power frequency (MPF), the 2nd moment about zero (V0), and the 3rd moment about zero (V03). For the one-sided Student t test with 8 degrees of freedom, $t \geq 1.860$ will show a .05 level of significance.

Tables II and III are summaries of the kind of data presented in Table I for all ten subjects. Table II shows the percentage of times that a parameter was significantly influenced by the presence of heart sounds. For example, from Table II it can be seen that in seven of the ten subjects, the average MPF's for expirations were significantly reduced when heart sounds were included ($\alpha = 0.05$). It is interesting to note that, for the parameters most likely to indicate heart sound contribution (MPF, V0, V03, F50 and F100), inspirations seemed less susceptible than expirations to heart sound interference. To a certain extent, this supports two observations made in the laboratory. One observation was that, in most subjects,

TABLE Ia

Mean Parameter Values with Standard Deviations and Results of Student t Tests for Subject #1

Parameter	Expirations w/o Heart Sounds Mean	Expirations w/o Heart Sounds S.D.	Expirations w/ Heart Sounds Mean	Expirations w/ Heart Sounds S.D.	Results of Student t Test
MPF	414.8	41.9	366.9	19.2	2.323
VO	451.8	37.9	411.8	12.6	2.238
VO3	483.0	33.2	449.4	8.3	2.198
VM	178.3	7.1	186.2	12.5	-1.234
VM3	75.8	100.4	141.6	21.9	-1.433
MXFP	329.4	96.2	280.4	94.2	0.814
SUM	205.3	46.5	446.8	177.3	-2.945
F50	0.15	0.05	1.20	0.31	-7.482
F100	4.50	2.81	6.70	2.31	-1.348
F150	4.76	2.18	9.01	5.33	-1.651
F200	7.74	5.44	12.56	3.03	-1.732
F250	9.96	2.49	11.29	2.46	-0.849
F300	9.70	1.65	9.74	3.51	-0.020
F350	10.73	3.31	6.32	3.02	2.199
F400	8.01	0.62	7.82	1.87	0.218
F450	8.40	1.63	8.51	3.51	-0.064
F500	9.76	2.51	7.25	1.82	1.807
F550	8.61	2.65	7.52	1.34	0.825
F600	6.86	2.00	5.57	0.53	1.392
F650	5.91	2.78	3.33	0.76	1.992
F700	4.07	1.38	3.36	1.23	0.861
F750	3.21	1.16	2.02	0.72	1.960
F800	1.34	0.42	1.12	0.11	1.094
F850	0.71	0.23	0.60	0.07	1.017
F900	0.23	0.07	0.17	0.04	1.612

TABLE Ib

Mean Parameter Values with Standard Deviations and Results of Student t Tests for Subject #1

Parameter	Inspirations w/o Heart Sounds		Inspirations w/ Heart Sounds		Results of Student t Test
	Mean	S.D.	Mean	S.D.	
MPF	240.4	11.2	228.5	2.6	2.308
VO	279.0	12.6	265.9	5.9	2.108
VO3	322.5	12.4	308.1	9.6	2.054
VM	141.7	6.0	136.0	8.1	1.257
VM3	173.1	3.4	166.8	10.6	1.260
MXFP	170.0	9.8	156.6	18.4	1.435
SUM	779.0	251.3	934.5	400.4	-0.735
F50	0.35	0.14	1.02	0.21	-5.924
F100	13.11	2.92	16.53	3.03	-1.818
F150	26.25	5.33	28.42	4.01	-0.729
F200	23.88	3.73	22.34	7.80	0.398
F250	12.21	3.03	11.71	1.63	0.321
F300	8.17	1.61	6.72	1.90	1.300
F350	4.29	1.61	4.78	0.62	-0.633
F400	3.07	0.94	2.70	0.75	0.691
F450	2.78	0.99	2.62	0.31	0.348
F500	2.27	0.73	2.06	0.48	0.542
F550	1.91	0.44	1.37	0.14	2.593
F600	1.17	0.31	1.01	0.18	1.050
F650	1.07	0.18	1.06	0.25	0.041
F700	0.96	0.20	0.96	0.41	0.006
F750	0.59	0.18	0.43	0.16	1.538
F800	0.44	0.14	0.31	0.16	1.294
F850	0.27	0.09	0.14	0.04	2.895
F900	0.08	0.04	0.05	0.02	1.637

TABLE II

Percentages of Times that Parameters were Significantly Affected by the Presence of Heart Sounds

Parameter	MPF	VO	VO3	VM	VM3	MXFP	SUM	F60	F100	F150	F200	F250	
Expiration	70%	50%	50%	10%	0%	10%	30%	90%	60%	10%	0%	10%	
Inspiration	50%	30%	20%	20%	20%	10%	20%	60%	30%	10%	30%	0%	
Parameter	F300	F350	F400	F450	F500	F550	F600	F650	F700	F750	F800	F850	F900
Expiration	20%	20%	20%	20%	20%	20%	0%	0%	0%	0%	10%	20%	20%
Inspiration	10%	30%	20%	10%	20%	30%	10%	20%	20%	20%	0%	20%	30%

inspirations were much more forceful than expirations, making for more total energy as indicated by the SUM parameter. Accordingly, heart sound contribution would be a smaller percentage of the total energy involved. A second observation was that, in some subjects, the act of inspiration had a visible muffling effect on the heart sounds as picked up at the trachea.

Table III shows the results of a statistical comparison of the differences in the average parameter values for all ten subjects ($\alpha = 0.05$). A paired difference t test with 9 degrees of freedom was used for the comparison. Most of the parameters show similar tendencies in both direction and magnitude regardless of whether inspirations or expirations were used. A few, however, show marked differences. In most of these cases, the differences are probably more readily attributable to differences in the sample breaths used than to intrinsic dissimilarities in the affect of heart sounds on expirations as opposed to inspirations.

Although there was often much variation in the data from subject to subject, when analyzed as a group certain trends are evident. The mean power frequency (MPF), which is a measure of the central tendency of the power distribution, is consistently lowered when the relatively low frequency heart sounds are included. This should be observed only if the contribution of heart sounds is

TABLE III

Comparison of the Differences in the Average Parameter Values Across All Ten Subjects Using a Paired Difference t Test

Parameter	MPF	VO	VO3	VM	VM3	MXFP	SUM	F60	F100	F150	F200	F250
Result of t test performed on inspirations	4.033	3.984	3.838	2.667	0.499	0.901	-1.093	-3.427	-4.360	-1.505	4.191	2.638
Result of t test performed on expirations	4.190	4.403	4.496	-0.046	-1.094	1.774	-1.224	-2.760	-4.991	0.100	0.679	1.607

Parameter	F300	F350	F400	F450	F500	F550	F600	F650	F700	F750	F800	F850	F900
Result of t test performed on inspirations	0.943	2.518	2.193	1.666	2.643	2.296	2.326	1.371	0.136	2.028	2.617	1.592	1.218
Result of t test performed on expirations	2.317	2.094	2.157	1.718	2.121	2.324	1.255	1.910	1.833	1.921	1.483	1.273	1.221

substantial enough to significantly shift the relative distribution of power down toward the y-axis. V0 and V03, measures of the distribution of power with respect to the y-axis, both show significant changes, as well. This lends more support to the idea that heart sounds are contributing energy at frequencies greater than 100 Hz. VM and VM3 are the 2nd and 3rd moments about the MPF, respectively. These parameters should be altered only if heart sounds, in addition to shifting the relative distribution of power, also act to concentrate the data around the MPF or vice versa. Although VM for expirations is altered significantly, it is not a strong tendency. It may be said, then, that including heart sounds does not generally cause a concentration or dispersal of data around the MPF.

MXFP is a parameter that locates the midpoint of the 50 Hz band that contains the maximum amount of power. It is difficult to predict in advance how great an affect heart sounds would have on this parameter. However, if it can be said that the intensity of heart sounds gradually tapers off as frequency increases (see references 1 and 2), then it might be expected that heart sounds would tend to slightly lower the MXFP of the respiratory sound signal. From Table III it can be seen that including heart sounds does indeed produce a small decrease in the MXFP across the ten subjects.

SUM is a measure of the total power found in a breath segment. Since it was not controlled for in this study, "heavier" breaths and "lighter" breaths should be randomly distributed within a subject's data. Therefore, no significant differences in SUM between data with and without heart sounds should be seen. This is borne out by both Tables II and III.

The remaining parameters, referred to as the "F" parameters, give the percentage of the total power found in the 50 Hz band centered at the indicated frequency. The "F" parameters seem to follow a predictable pattern overall. The low frequency bands, where heart sounds should contribute the greatest amount of their energy, contain larger percentages of the total power when heart sounds are included. As a result, the higher frequency bands must contain relatively less energy. It is interesting to observe that it is the band centered at 150 Hz that seems to be the last one affected by the contribution of heart sounds. This might indicate that it is around this frequency that heart sound interference becomes insignificant, although one cannot determine this from the data as presented since it is based on percentages. Another interesting observation is that the F50 band contains only a very small amount of the total power, the result primarily of the digital high-pass filter used. However, the F100 band, which includes the frequencies from 75-125 Hz, contains a large amount of the total power in most subjects. As a rough estimation of the error being introduced, it might be advantageous to center a 50 Hz band at 75 Hz to see how much of the total power is found at the frequencies from 75-100 Hz.

CONCLUSIONS AND RECOMMENDATIONS

Based on the results obtained, the hypothesis that heart sounds do not significantly affect respiratory sound data at frequencies greater than 100 Hz must be rejected. The parameters that should deviate if the presence of heart sounds were significant (MPF, V0, V03, F100) did, in fact, do so. Two immediate implications are as follows:

1) Past studies in which heart sound interference was not controlled for or not controlled for adequately (i.e. - Charbonneau, who used a cutoff frequency of 60 Hz and an attenuation slope of 48 dB/octave [see reference 3]) may have had a significant source of error introduced into the results. It could be speculated that this would be equally true for studies in which sound was recorded at the chest wall, although the current research can contribute no direct evidence as all data was collected at the trachea.
2) A design consideration for any device that proposes to analyze respiratory sound data must be to compensate for heart sound interference at frequencies greater than 100 Hz. Such compensation might be achieved by

filtering, by inverting the heart signal and subtracting it out, or by sampling respirations between heart sounds.

Future research in this area might include an investigation into the differences in breath sound as a function of the position in the breath. As stated earlier, with the exception of avoiding the extreme ends of breaths, no effort was made to control this variable. Typically, the variance of the average of the four FFT's performed on a given breath segment was quite small, however, this might not remain true if the sampling time were increased.

Also of interest are causes of the great differences seen in data from subject to subject. Since the physiologies of the subjects involved are almost certainly primary contributors to these variations, investigations into the role of physiology in respiratory sound production could prove fruitful. Finally, in this study, five subjects exercised aerobically on a regular basis and five did not. A comparison of these two groups might have implications in the future use of sound data as a diagnostic tool.

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APPENDIX I

Biodata of Subjects Used in this Study

Subject #	Height and weight	Age	Do you presently smoke	Have you ever smoked regularly	Do you have any history of resp. disease	Do you have any history of heart problems	Have you had any recent illness	How much exercise do you get in a week
Subject #1	6'1" 180 lbs.	21	No	No	No	No	No	None
Subject #2	6'2" 175 lbs.	22	No	No	No	No	No	5 hrs./wk. - aerobic (running)
Subject #3	5'8" 135 lbs.	22	No	No	Very occasional Asthma	No	No	2 hrs./wk.
Subject #4	5'11" 185 lbs.	22	No	No	No	No	No, but sinuses not completely clear	2 hrs./wk.
Subject #5	6'2" 185 lbs.	22	No	No	No	No	No	<5 hrs./wk.
Subject #6	6'2" 165 lbs.	25	No	No	No	No	No	>5 hrs./wk. - aerobic and anaerobic
Subject #7	6'0" 170 lbs.	24	No	No	No	No	No	>10 hrs./wk. - aerobic (bicycling)
Subject #8	6'4" 200 lbs.	22	No	No	No	No	No	12-15 hrs/wk. - aerobic (bicycling)
Subject #9	6'0" 165 lbs.	22	No	No	No	No	No	10 hrs./wk. - aerobic (bicycling)
Subject #10	6'2" 155 lbs.	25	No	No	positive test for TB 4 yrs. ago, but no evidence presently	No	No	2 hrs./wk.

APPENDIX II

Description of Parameters

MPF - mean power frequency $\left(\frac{\sum(c_i^2 \cdot i)}{\sum c_i^2}\right)$; where i = 0, 1, 2 ..., N-1 and N is number of samples used in the FFT (824)

V0 - 2nd moment with respect to zero $\left(\sqrt{\frac{\sum(c_i^2 \cdot i^2)}{\sum c_i^2}}\right)$

V03 - 3rd moment with respect to zero $\left(\sqrt[3]{\frac{\sum(c_i^2 \cdot i^3)}{\sum c_i^2}}\right)$

VM - 2nd moment with respect to the MPF $\left(\sqrt{\frac{\sum(c_i^2 \cdot (i-MPF)^2)}{\sum c_i^2}}\right)$

VM3 - 3rd moment with respect to the MPF $\left(\sqrt[3]{\frac{\sum(c_i^2 \cdot (i-MPF)^3)}{\sum c_i^2}}\right)$

MXFP - midpoint of the 50 Hz band that contains the maximum amount of power

SUM - sum of the total power found in a breath segment

F50-F900 (the "F" parameters) - percent of energy occurring in the band $\pm$ 25 Hz from the designated frequency

(c_i is the complex coefficient of the Fourier series and has the units of volts.)