University of California

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Pitch Correction for the Human Voice

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Bachelor Of Science

in

Physics

by

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Contents

Abstract

Pitch correction for musical applications is a new and extremely influential technology. Since the introduction of Antares' Auto-Tune in 1997, the music recording industry has been completely revolutionized by the ability to correct out of tune vocals. This paper examines some of the mathematical and computational techniques behind pitch correction. Methods of pitch estimation and pitch correction in both the time domain and frequency domain are discussed with an emphasis on their application to musical singing.

1 Foreword: A Bit of Terminology

In discussing mathematics along with music it's often easy to get lost in terminology. For this reason, I've relaxed a few definitions regarding sound and singing in the body of this work. Although the terms "pitch" and "frequency" are known to have slightly different definitions[1], for ease of discussion the two shall be used interchangeably. In addition, the complicated process of human singing is indeed very similar to the process of speech. Throughout this paper, then, the term "speech" may be used to mean "voiced singing," or vice-versa.

2 Introduction and Background

Humans have been using their voices to create musical pitch for thousands of years. With the invention of recorded sound by Thomas Edison in 1877 came the advent of musical recordings featuring some of the world's greatest artists. From that time on, one could experience the mastery of great vocal works without needing to be present at the location of the performance. As recording technology developed with the multi-track recorder, high fidelity records became more and more available to the masses. Over time, studio engineers developed techniques to alter sounds during the recording and mixing process. Often these alterations were designed to make a performance sound more "real," but were sometimes aimed at creating new sounds which were impossible to produce without the use of modern computers. Artificial reverb is a good example of something designed to simulate "natural

[1]Whereas frequency is an absolute measure of rate, pitch is a relative term used often in music to relate one note to another.

sound," while the electronic synthesizer is often used for synthetic music production. Recently, computer technology has made it possible to alter the sound of the recorded voice in ways heretofore unimaginable. Many effects have been applied to recorded singing, but the most influential by far has been the introduction of pitch-correction software.

Pitch correction is exactly what it sounds like: A vocal performance is altered by a computer such that every note is reproduced with perfect pitch. What this means is a singer can make a mistake in pitch during the recording process and a computer, using a variety of algorithms, can "correct" the pitch of the fouled note. This can, in fact, be used to correct several mistakes or even an entire performance if a singer has the tendency to sing out of tune. What's more, with modern computer chips this process can be done in real-time[2] and pitch can be corrected during a live performance!

This paper gives an in depth look at the computational methods behind pitch correction. Techniques are discussed for analyzing and processing audio in both the time domain and the frequency domain. The pitch-synchronous overlap and add method and the modified phase vocoder are investigated in detail, and pitch detection algorithms are explained.

3 Introduction to Musical Pitch and Sound

The idea of musical pitch is directly related to the concept of frequency. The human ear can detect sound frequencies between around 15 and 20,000 Hz. It is assumed the reader has a basic understanding of sound waves and how they propagate through air, but it's important to remember that at any time, your ear is only subject to one given air pressure level. As sound waves pass by, the air pressure at the ear changes in accordance with the wave. This change or oscillation is what is recorded by microphones, and, eventually, encoded digitally as a string of numbers as will be explained here in the section on Pulse-Code-Modulation.

[2]Here, what is meant by real-time is an imperceptible delay between the source signal input and the processed signal output.

3.1 Timbre

Another important aspect of musical sound is the idea of *timbre*. Timbre is a psychoacoustic phenomenon that is best described as the "color" or "tone" of a pitch, also known as the "character" of a sound. Timbre is what distinguishes a piano's sound from, say, a saxophone's. Both instruments playing the same pitch (note) are easily distinguishable because each has a unique timbre. From a technical standpoint, timbre is related to the frequency spectrum of a sound. When an instrument produces a particular pitch, such as A4 (defined to be 440Hz), a series of *overtones* are produced depending on the instrument and technique used to play it. These overtones are often integer multiples of the note intended and are what give the particular instrument its "color." The intended note is called the *fundamental frequency* and the overtones are also called *harmonics*. Of interest to this paper is that the human voice also produces harmonics when singing. These harmonics are also called "overtones," or "formants." Formants are, in fact, the main attributes which enable listeners to distinguish between different singers. The concepts of fundamental frequency and overtones are important to any pitch correction system and will be expanded upon in the section regarding pitch-estimation.

4 Basics of Digital Audio and Spectral Analysis

4.1 Encoding digital audio - Pulse Code Modulation

Before discussing the techniques of pitch correction it's important to have an understanding of how sound is recorded digitally. The most basic form of digitized sound is called Pulse Code Modulation, or PCM. Pulse Code Modulation stores an analog signal in discrete time steps with discrete amplitudes. Whereas an analog sound wave is continuous, a computer can only store discrete values. The digitization process goes as follows: A sound source is recorded by a microphone, which induces a current in a wire. An analog to digital converter (ADC) takes the incoming signal and samples it at a given frequency, F_s. Each sample is stored as a particular value, and the next sample is taken. The number of values available

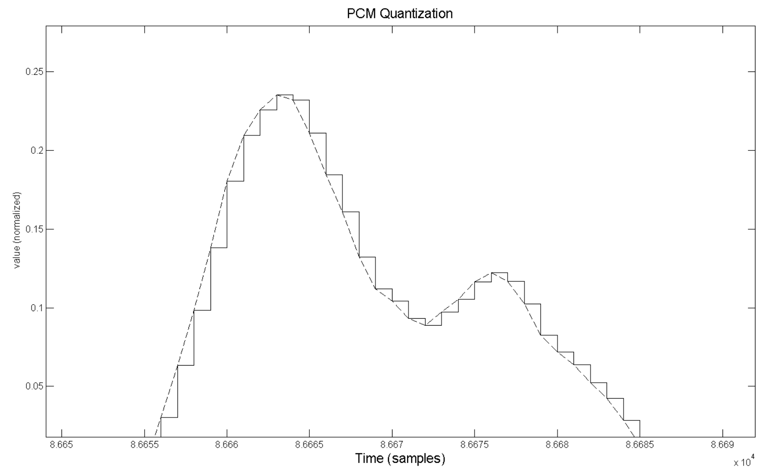

Figure 1: Illustration of quantization errors as a result of PCM encoding. Original waveform is marked by dashed line, encoded signal marked by solid line. Note the discontinuities in PCM waveform will translate to extremely high frequencies in the Fourier Transform frequency spectrum, hence a low-pass filter is applied.

can be thought of as the amplitude resolution of the ADC, which depends on the ADC itself. For example, an 8-bit ADC can store $2^8 = 256$ different values, and a 16-bit converter can distinguish between $2^{16} = 65,526$ values. One can imagine the sound quality of a 16-bit ADC to be far superior to an 8-bit chip when both are operated at the same sampling frequency. For traditional CDs, $F_s = 44,100$ Hz with 16 bits of amplitude resolution.

The inherent nature of storing audio digitally means that some approximations must be made. The process of taking an analog signal and associating with it specific values within the range available by the coding process is called *quantization*. Quantization introduces frequency components into the recorded signal that weren't necessarily present in the original waveform. Because of this, signals are often processed by a low-pass filter, which filters out the high frequency components. An illustration of a PCM waveform with quantization error is shown in figure 1.

It should be understood now that audio stored on a computer in PCM form is essentially a long string of values corresponding to a sequence of particular currents or voltages, with one stored value for every $1/F_s$ of a second. To listen to the audio, the reverse process takes place: The string of values is decoded by a Digital-to-Analog converter (DAC) and is output as a voltage or current on a wire. This voltage can be amplified to drive a speaker, producing the recorded sound. It's important to realize that digital sound is stored in discrete values to appreciate the need for the Discrete Fourier Transform.

4.2 The Discrete Fourier Transform

Fourier analysis is one of the most important mathematical techniques in signal processing. The Fourier transform presents a way of converting a signal in the time-domain to one in the frequency domain. That is to say: it takes a function of a real variable (time) and turns it into a function of frequency. The Fourier transform of an audio signal often has complex values, which are representative of amplitude and phase information. The plot of frequency vs. the absolute value of the complex outputs of a Fourier transform can be thought of as a power spectrum. The power spectrum is a sort of fingerprint of the original signal, as it's snapshot of the frequency components present in the original signal. Fourier showed that any periodic function can be broken up into its constituent frequencies in this manner.

Since computer audio signals record amplitude at discrete time values, a technique called the Discrete Fourier transform (DFT) is implemented to analyze digital audio[3]. The DFT is therefore a discrete-valued version of the Fourier transform. A common form of the DFT is found below:

$$x[n] \equiv x\left(nT_s\right) = \frac{1}{N}\sum_{k=0}^{N-1} X[k]e^{i2\pi kn/N}, n = 0, 1, 2, ..., N-1 \tag{1}$$

$$X[k] \equiv F_s X\left(kF_s/N\right) = \frac{1}{N}\sum_{n=0}^{N-1} x[n]e^{-i2\pi kn/N}, k = 0, 1, 2, ..., N-1 \tag{2}$$

In this format, $x[n]$ is a discrete valued function of time and can be thought of as the original sampled audio. N is the total number of samples, F_s is the sampling frequency, $T_s = 1/F_s$ is the sample length, and the total signal duration is $T = N \times T_s$. $X[k]$ is therefore the transform of $x[n]$, and is a function of frequency k. The Discrete Fourier transform is capable of resolving frequencies up to N/2 Hz.

4.2.1 The Fast Fourier Transform

The Fast Fourier transform, or FFT, is an implementation of the Discrete Fourier Transform. It gets its name because of its ability to greatly reduce the number of computations needed to perform a DFT. A DFT of N samples takes $N \times N = N^2$ complex multiplications and additions to carry out, while a DFT reduces the problem to roughly $Nlog_2(N)$ complex multiply-adds [3]. The great computational efficiency of the FFT led to advancements in signal processing and the possibility of complex real-time processing[3]

5 Pitch Estimation Methods

5.1 Goals of a pitch estimation algorithm

The first step in altering or correcting the pitch of a voiced signal is to properly identify the note being sounded or sung. After all, in order to shift from one frequency to another, one must indeed know the original frequency. Determining this is no trivial task, and much work has been done in pitch-estimation theory. Applications of pitch determination aren't limited to music. In fact, this type of analysis is important for all types of signal processing and some engineering work. Pitch estimation uses any and all tools available to determine the fundamental frequency F_s. Often, a knowledge of typical frequencies present in the signal can help optimize pitch-estimation algorithms. In the case of musical singing, these frequencies range from a low bass at around 80 Hz to a high soprano at 1,100 Hz, or E_2 to C_6 on the piano. It's important to note that a typical sampling frequency of 44.1 kHz is more than adequate to resolve fundamentals in this range. For example, a 1,000 Hz wave will have $F_s/1,000 \simeq 44$ samples to represent one full period as seen in figure 2.

Of course, the human voice doesn't produce a perfect sine wave. Instead it produces a complex waveform which contains a fundamental frequency, F_0, with a signature of harmonics unique to the individual singer. While some of these harmonics may be outside the resolvable range, it is the fundamental which is sought by the pitch-estimation algorithm.

[3]For further reading on Fast Fourier Transforms see [3] [1] or any thorough signal processing text.

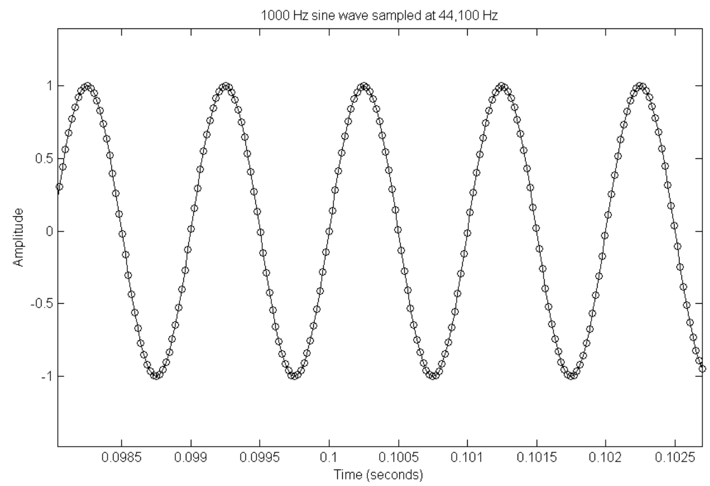

Figure 2: 1000 Hz sine wave sampled at 44.1 kHz. Sample points are marked by $\circ$.

5.2 A Few Technicalities

Any pitch estimation algorithm takes a discrete signal $x(n)$ as an input. $x(n)$ is often a sampled version of the original continuous signal $x(t)$. From here on we'll be working primarily with the sampled signal $x(n)$ and its discrete Fourier transform $X(k)$. Remember that n is the sample number, and the amount of time between successive samples is the sample period $T_s = 1/F_s$. In this way, n is a time variable, so $x(n)$ is a function of time. As an example, a one second recording with a sampling rate of F_s =44.1 kHz will produce 44,100 total samples, which we call $N = \#$ samples. The range of n, then, is $1 < n < N$.

In the frequency domain, the variable k represents individual frequencies. More precicely, k translates to actual frequencies f in Hz as

$$f = \frac{kF_s}{N}.$$

So $X(k)$ gives amplitude and phase information as a function of frequency. A common way of visualizing the transform $X(k)$ is to plot the absolute value of X, which is a representation of the amount of energy present at each frequency. It's also important to note that a discrete Fourier transform of length N samples is only capable of analyzing frequencies up to a certain frequency, callded the Nyquist frequency:

$$f_{Ny} = \frac{1}{2}\frac{kF_s}{N}.$$

This is due to the fact that frequencies from f_{Ny} to $2f_{Ny}$ in the transform are actually reflections of frequencies in the range $0 < f < f_{Ny}$. The Nyquist frequency is usually half the sampling rate, $f_N y = F_s/2$ and is a fundamental property of sampling theory. The idea is that the highest frequency one can digitally encode given a certain sampling rate is a signal oscillating at half that rate [10].

5.3 Windowing

One of the most fundamental processes in signal processing is the breaking up of a discretely sampled signal into smaller constituents or "windows." In the context of pitch-correction, windows are analyzed and processed individually, then recombined to produce a coherent output. For example, to determine the pitch of a particular vocal passage, the signal is divided into windows of lengths on the order of a few pitch-cycles. The fundamental frequency of each window is then found and used to process the final output. The most simple method of *windowing*, as it's called, is to take the samples exactly as they are in the original and divide them into groups. This can be thought of as multiplying the signal by a rectangular windowing function:

$$w(n) = \begin{cases} 1 & , 0 < n < N \\ 0 & , elsewhere, \end{cases}$$

where n is the sample number, and N is the total number of samples per window (window size). The problem with this type of window involves advanced topics in Fourier analysis, but can be summarized by saying that the transform of a signal windowed by the function above will contain energy at frequencies not actually present in the original signal [3]. In fact, *any* window function will introduce new frequency components to a windowed signal.

The goal, then, is to use a window function which minimizes these effects.

One useful window is the Hamming window, defined by:

$$w_H(n) = 0.54 + 0.46 \cos\left(\frac{2\pi N}{N-1}\right),$$

offers reasonable results for our application. In the process of dividing up the original signal into smaller pieces, then, a window function is usually applied as $x(n)w(n)$.

Another application of the window function comes into play when an overlap-add technique is employed. Often in signal processing, it's advantageous to window a signal in an overlapped manner, where each segment contains some of the same information as its nearest neighbors. By using an appropriate window function, these overlapping segments can be processed separately and eventually combined to produce a coherent output. Fig's. 3 and 4 show a sample of a raw PCM waveform about 0.9 seconds long plotted before and after windowing. The Hamming window is also plotted in Fig. 3 for reference.

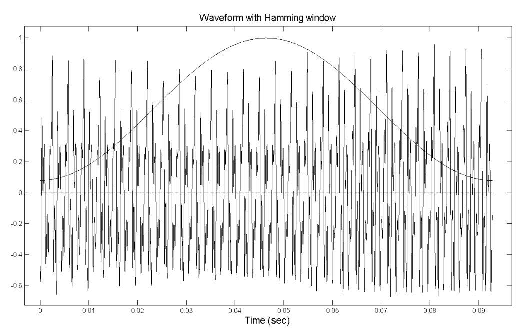

Figure 3: Original waveform and Hamming window shape.

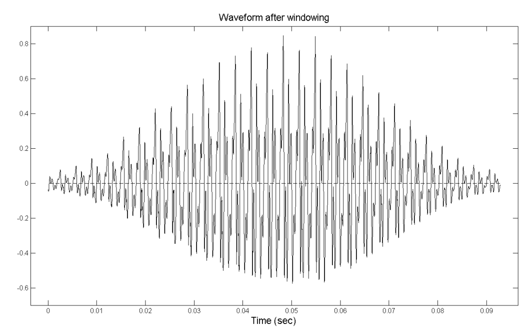

Figure 4: Waveform after scaling by Hamming window.

5.4 The two types of pitch estimation methods

Pitch estimation methods can be broken up into two distinct categories: time-domain methods and frequency-domain methods. Time domain methods analyze audio signals in their native form - amplitude as a function of time, or $x(n)$. In general, they look for repeated patterns and associate the interval of repetition with a fundamental frequency. Frequency-domain methods, on the other hand, perform a transform operation on the signal and seek the fundamental by analyzing the audio in the frequency domain, $X(k)$.

5.5 Time Domain Pitch Determination Algorithms

5.5.1 Basics of Time-Domain PDAs

As mentioned above, time-domain pitch determination algorithms work entirely in the time-domain. Most operate on the idea that a spoken or voiced signal has a great degree of periodicity and that the shape of the repeated waveform will not change much from once cycle to the next. By comparing adjacent parts of the signal one can estimate the fundamental frequency. Some algorithms merely look for two adjacent "high peaks" in the wave form and estimate the distance between them as the fundamental period $T_0 = 1/F_0$.

5.5.2 Average magnitude difference method

Another basic approach to frequency estimation is the average magnitude difference function. The premise behind this method is that the average magnitude of a signal will remain almost the same from one period to the next. The average magnitude difference function (AMDF) [5] is defined by:

$$A(\tau) = \sum_{n=0}^{N-1} |x(n) - x(n-\tau)| \tag{3}$$

where τ is the "lag" and is allowed to vary over a predetermined range. The AMDF compares the signal throughout a frame with itself shifted by a time τ. The value of τ which minimizes $A(\tau)$ is chosen as the pitch period. This works on the presumption that a periodic signal produced by the voice will vary only slightly from one pitch cycle to the next. Computationally, the AMDF is very lightweight, making it ideal for hardware applications and real-time processing.

5.5.3 Autocorrelation Method

The autocorrelation method is similar to the AMDF in that it finds the period T_0 by comparing the waveform with itself shifted by a time τ. The difference being a more sophisticated method of comparison. The derivation of the normalized autocorrelation function is well explained in [5], while a summarized version is presented here. A basic method of comparing two waveforms is called the direct distance method:

$$E(\tau) = \frac{1}{N} \sum_{n=0}^{N-1} [x(n) - x(n+\tau)]^2.$$

Similarly to the AMDF, the value of τ which minimizes the error $E(\tau)$ is chosen as the fundamental period T_0. This technique works well, but often fails at portions of speech with quickly varying energy levels, such as at speech onsets and offsets. To compensate for this, a scaling factor β is introduced:

$$E(\tau) = \frac{1}{N} \sum_{n=0}^{N-1} [x(n) - \beta x(n+\tau)]^2.$$

β is found by setting $\delta E(\tau, \beta)/\delta(\beta) = 0$ [5]. With this new factor defined, the error becomes:

$$E(\tau, \beta) = \sum_{n=0}^{N-1} x^2(n) - R_n^2(\tau)$$

where

$$R_n^2(\tau) = \frac{\left[\sum_{n=0}^{N-1} x(n)x(n+\tau)\right]^2}{\sum_{n=0}^{N-1} x^2(n+\tau)}.$$

Minimizing $E(\tau, \beta)$ is then the equivalent of maximizing $R_n^2(\tau)$. As one last detail, the square root of $R_n^2(\tau)$ is taken to avoid possible maxima where the correlation is in fact negative. The result is therefore:

$$R_n(\tau) = \frac{\sum_{n=0}^{N-1} x(n)x(n+\tau)}{\sqrt{\sum_{n=0}^{N-1} x^2(n+\tau)}}.$$

Again, the value of τ which maximizes $R_n(\tau)$ is chosen as the fundamental period. This pe-

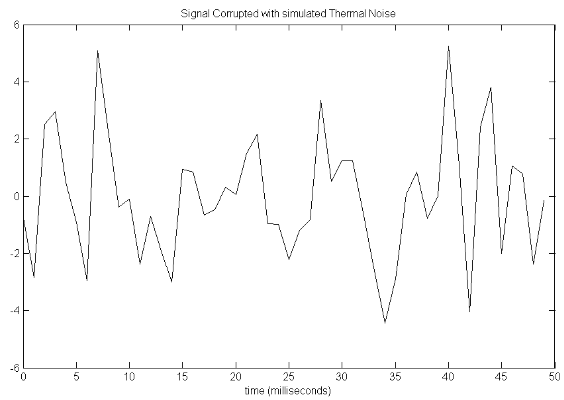

Figure 5: Note: the sinusoids are almost impossible to recognize.

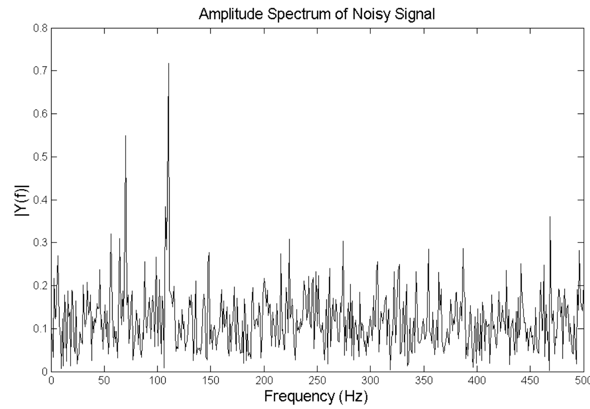

Figure 6: Power spectrum showing clear spikes at 70 Hz and 110 Hz.

riod is inverted to obtain the fundamental frequency F_0, which is used in the pitch-correction stage.

5.6 Frequency-Domain Pitch Detection Algorithms

5.6.1 Basics of Frequency-Domain PDAs

Despite their computational cost, FFTs along with today's fast computers have made signal processing in the frequency domain a practical reality. A transform to the frequency domain will often reveal features of a signal which are nearly impossible to detect otherwise. For example, a sinusoidal signal traveling along a wire can become subject to thermal noise. Visual inspection of the incoming waveform may suggest the signal has no regular periodic component, but a Fourier transform will immediately identify the sinusoidal element. The signal in figure 5 was generated by adding two sinusoids with frequencies 70 Hz and 110 Hz and zero-mean random noise. The frequency components are nearly impossible to recognize in this form. A FFT was performed to yield the spectrum displayed in figure 6. There are clear spikes in the plot at 70 Hz and 110 Hz, corresponding to the periodic components present in the original signal. This example illustrates the potential power and effectiveness of analyzing signals in their frequency domains.

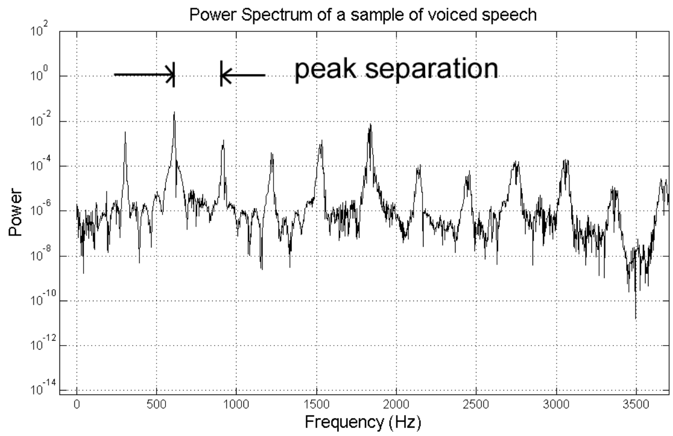

Figure 7: The distance between peaks in the spectrum analysis is indicative of F_0

5.6.2 Harmonic Peak Detection

The harmonic peak detection method seeks the fundamental frequency by looking for peaks in the frequency spectrum separated by equal distances. The theory behind this is the idea that most harmonics present in a signal have frequencies which are integer multiples of the fundamental. By applying a comb filter and tuning the filter to match the peaks in the spectrum, one can obtain a good estimate of the fundamental as either the distance between peaks or the common divisor of the harmonics [5]. Fig. 7 shows a power spectrum of a window of speech and points out size of repeated peaks.

5.6.3 Spectrum Similarity

The spectrum similarity method detects pitch by comparing a signal with an idealized model. The method assumes the incoming signal to be fully voiced and comprised only of harmonics at integer multiples of the fundamental [5]. A synthetic signal is established for a range of frequencies and compared with the actual spectrum. The frequency which causes the model to best match the real spectrum is selected as the fundamental. This process is analagous to the autocorrelation method used in the time domain.

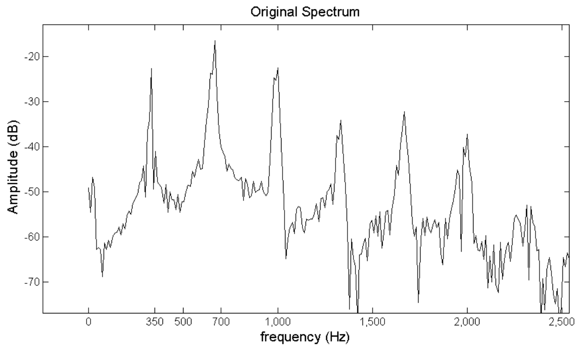

Figure 8: Original frequency spectrum suggests $F_0 \simeq 700$ Hz.

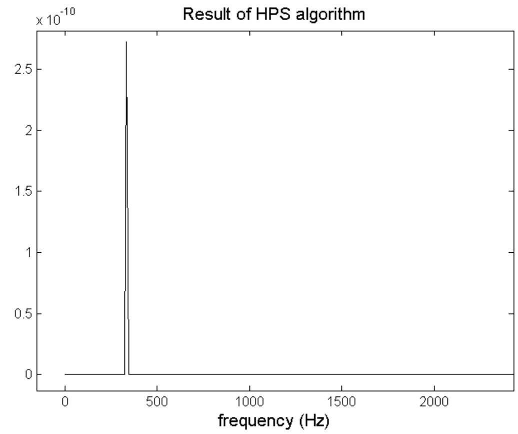

Figure 9: DFT of DFT correctly identifying $F_0 \simeq 350$ Hz.

5.6.4 Harmonic Product Spectrum

Almost all pitch estimation methods that operate in the frequency domain look for evidence of repeated peaks in the spectrum. Gareth Middleton exploited this fact in his paper on pitch correction in which he compared scaled frequency spectra of samples in a process called harmonic product spectrum (HPS) analysis [8]. HPS analysis involves compressing a spectrum in a process called *downsampling* and multiplying these new spectra with the original. The cumulative effect of multiplying the spectra together can render a prominent frequency spike at the location of F_0. In a test case produced for this work, the HPS algorithm succesfully identified a fundamental frequency near 350 Hz where the original power spectrum suggested a fundamental of $\simeq$ 700. Fig. 8 shows the spectrum for the sample of speech with a clear spike around 700 Hz. Fig. 9 is the result of applying a 3^rd order HPS algorithm to the spectrum, meaning the original DFT plot was resampled, stored, and multiplied three times. The fundamental is known because, among other reasons[4], it can be extracted by inspection from the original waveform shown in Appendix A as Fig. 13.

5.6.5 "DFT of the DFT"

Another interesting approcach comes from a paper by Ahlfinger, Cheeseman, and Doody in which the authors exploit the periodic nature of the fourier transform of a periodic signal.

[4]The sample is taken from a sung passage by this author in which the notes are well known.

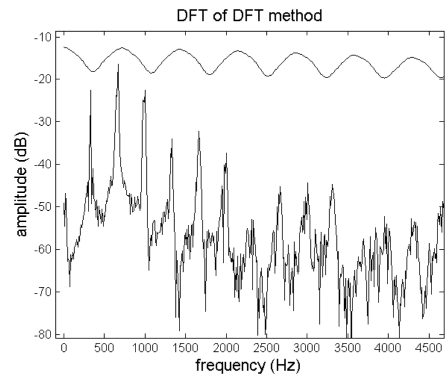

Figure 10: The 2nd peak in the DFT of DFT closely identifies the fundamental.

Again, The frequency spectrum of a periodic signal will exhibit a periodic nature much like that of an impulse train, though ususally much more complicated. By taking another discrete Fourier transform on the spectrum, Ahlfinger, et. al. were able to effectively measure this period as the fundamental from the original signal [13]. A basic script for calculating DFT of DFT was written to produce the plot in Fig. 10. The highest peak other than the one centered at zero is chosen as F_0.

5.7 One Other Criterion: Classification of Voiced/Unvoiced Speech

The methods thus far have focused on pitch estimation and determination. While finding the fundamental frequency is of utmost importance, there is one other factor which will help the pitch-correction algorithm produce a satisfactory result. Human speech is an extremely complicated process but it can, for simplicity (and sanity), be broken into two distinct forms: voiced and unvoiced. Voiced speech is the most tonal portion and occupies most of our speech. Unvoiced speech refers to those moments where the airflow is briefly interrupted or a signal with highly un-periodic characteristics are made, such as the "g" in "great," or the "s" in "sound." The observant reader will note that there are additional unvoiced sounds in these examples: the "t" at the end of "great" and for a brief moment during the "d" in "sound." One might argue that these are indeed periodic signals with extremely high frequencies. Analysis has shown that not to be the case, however, and these parts of speech are best modeled by a form of white noise.

Several algorithms have been developed to aid in the distinction between voiced and unvoiced sounds. For a good overview see *Digital Speech* by A. Kondoz [5]. The most basic of these looks for the general feature of periodicity in a signal. It is similar to the autocorrelation method discussed before, but in this case a threshold is set. Any window of signal which doesn't exhibit enough periodicity is determined to be unvoiced. In most pitch correction schemes unvoiced portions of the signal are left unaltered, while voiced parts are processed and re-synthesized.

6 Pitch Correction

6.1 Concepts of Pitch correction

The end-goal of all the above pitch estimation methods was to determine the fundamental frequency of voiced speech. Once this frequency is known, it can be used to accurately alter the pitch of the signal. Here it should be explained that most Western music uses what is called the *equal temperament scale*. This scale determines the pitches found on a piano keyboard, and is the result of many mathematicians' and musicians' work from the 1500's on [11]. For the purposes of this study it needs only be known that there are a set of predetermined notes which are considered "in-tune" for most music. As an example, the notes labeled $C2$ and $C\#2$ have frequencies 65.4064 Hz and 69.2957 Hz, respectively. If a cello played a note with a fundamental frequency of, say, 67.0 Hz, it would be considered "out of tune" since it isn't one of the allowed frequencies[5]. The same would go if a singer attempting to sing $C\#2$ made a note with fundamental frequency 67 Hz. His or her note would be described as "flat" because it has a frequency F_0 that is *less* than the desired pitch. On the other hand, if the attempted note were $C2 = 65.4064$ Hz, the 67 Hz pitch produced by the singer would be considered "sharp." The purpose of a pitch correction system, then, is to confine a singer's pitches to a set of predetermined "allowed" notes (frequencies), thereby making him or her always sound "in-tune."

Just as there are methods of determining fundamental frequency in both the time-domain

[5]67 Hz isn't allowed because there are no established notes between $C2$ and $C\#2$. There are exceptions to the rule, but they are ignored for simplicity in this study.

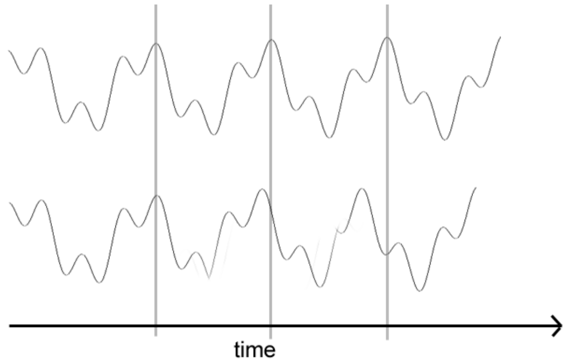

Figure 11: A rough diagram of wavelength shortening (pitch increase) by PSOLA

and frequency-domain, so, too are there methods of correcting frequency in both domains. Both approaches have their merits and pitfalls as they are summarized below.

6.2 Time-Domain Pitch Correction

6.2.1 Pitch Synchronous Overlap Add

One very basic way of altering pitch is to play a sequence back at a different rate than it was recorded. For example, playing a 44.1 kHz file back at twice the rate, 88.2 kHz, will result in all pitches being doubled. The main problem with this method is that by effectively stretching or compressing the entire signal all the harmonics and formants of the voice also become affected. What this means in practice, is that an upward shift in frequency will result in a so-called "chipmunk effect" in which the singer sounds much different than he would if he were actually singing the higher note. The Pitch Synchronous Overlap-Add method (PSOLA) is an effective and computationally efficient algorithm which preserves the singer's natural harmonics.

The principle of the PSOLA method is to lengthen or shorten the waveform at a very small scale - often on the order of fractions of a period per few periods. The process goes as follows: The original signal is analyzed by a pitch-detection algorithm and the fundamental frequency of each window is established. Next, the waveform is given pitch-markers at intervals equal to the pitch period T_0. The markers are often placed at locations of the largest peak in each cycle. Next, a new sequence of markers is established based on the desired (target) frequencies. The synthesis process then involves matching the frequency markers in the sampled signal with the target markers. The original signal is then windowed, centering around every 2^{nd} or every 4^{th} marker, and each overlapped segment is added to the previous one to reconstruct a full signal with the new fundamental period (see Fig. 11 for a graphical depiction of this process) Any portion of the pitch deemed as unvoiced is simply copied directly with no modification. Note that while the traditional window size for pitch detection is around 90 ms long (4096 samples for 44.1 kHz audio), the windows used for synthesis in PSOLA are much smaller: For a 300 Hz fundamental frequency, four periods is equal to $4/300 \simeq 13.3$ms. The method of PSOLA thus corrects pitch while preserving most of the shape of the original waveform. Fig. 12 in the appendix shows a graphical timeline of the PSOLA algorithm.

6.3 Frequency-Domain Pitch Correction :The Modified Phase Vocoder

The most promising and effective pitch modification technique which operates in the frequency domain is called the *modified phase vocoder*. The term "vocoder" is short for "voice-encoder," as the original vocoder was designed in the 1930's to transmit secure communications. The modified phase vocoder is an expansion on the original concepts and is usually implemented digitally.

The analysis and synthesis process in the modified phase vocoder is as follows: A pitch detection algorithm divides the original signal into overlapping segments and stores the fundamental frequency for each in memory. The segments are then windowed and transformed by a FFT algorithm. The results of each transform are stored in a new matrix. A typical design would place the output for each frequency k in the transformed function along a column vector, with each column representing an individual window. The spectrum for each bin is then processed individually. An algorithm then detects all the peaks present in the frequency spectrum and shifts them by an appropriate factor - in effect altering the pitch of each window. The scaling factor is determined by the original detected frequency and the target frequency. A complex phasor is then multiplied to each peak and its surrounding region in order to preserve phase relationships across windows. Lastly, each column vector is overlap-added in a reconstruction process which produces the pitch shifted signal [2]MiddletonFrequency.

One great advantage of the modified phase vocoder is the ability to process polyphonic signals. Polyphonic signals contain more than one fundamental frequency, such as a chord played on a piano or the sound produced by two singers in harmony. In theory, the vocoder could correct one out-of-tune singer and leave the other's signal nearly unchanged. This has huge applications when applied to live sound recordings, which are often limited to a single stereo mix. The merits of this have yet to be seen in practice, but new technology from *Celemony* promises to do exactly this [14].

7 Comments and the Future of Pitch Correction

Any musician will tell you that perfect pitch is merely a theoretical limit - that no human can possibly sing with perfect pitch. Sure, some greats may come close, but the physiology of the human vocal tract makes it virtually impossible to sing without a single deviation in pitch. In some performances deviation from perfect pitch is even desired and can be used for emphasis, tension, or style in the music. The definitive piece of software in the world of pitch correction is "Auto-Tune," by Antares Technologies. Auto-Tune puts accurate, high quality pitch correction at recording engineers' fingertips with an easy to use interface and the ability to run on most computers. Since its introduction in 1997, Auto-Tune has revolutionized the music industry. It has sparked an ongoing debate which divides some of the world's top musicians and producers. On one side of the argument is the case that pitch correction is a form of cheating, in that it allows less-than-adequate singers to sound as if they have real talent. The other side argues the technology has provided greater workflow in the studio, greater records overall, and has allowed creative singers of all skill levels to present their music in a palatable form. The debate continues, but one thing is for sure: it's changed the way music is made.

I had the privilege of interviewing Antares' founder and chief scientist, Dr. Andy Hildebrand, and asked him about the direction of his technology. As the person responsible for Auto-Tune, Dr. Hildebrand feels a sense of satisfaction that he's completely altered the music industry. He doesn't forsee the immediate direction the technology will go, and admitted he had no idea the software would be used as a voice-altering effect as it often is today[6]. When asked about some of the criticism aimed at pitch correction, he kindly responded, "I'm an engineer, not an artist," suggesting that his goal was to write the software, not debate its use.

One other note of interest was Dr. Hildebrand's approach toward entrepeneurship. He earned his PhD. in electrical engineering and has years of experience with signal processing, from geophysics research in the oil industry to fixing sour notes in recording studios everywhere. He says some of best technology comes from innovators who see a goal and develop a means to that end. Auto-Tune, as it turns out, processes signals entirely in the time-domain. Dr. Hildebrand says this is the most computationally efficient method and is the reason his products are the only pitch-correctors that work in real-time for live applications.

8 Conclusion

This work presented an investigation into the methods behind pitch correction for the human voice. It isn't immediately obvious whether time-domain or frequency-domain algorithms are more effective. The general consensus in industry is to use whichever approach best suits the needs of a particular implementation. It's understandable to note that effective pitch correction suitable for music applications has only become available over the last ten years. With this in mind, it's exciting to imagine where the technology will be in another ten. Antares is in currently in development of an Auto-Tune based application for the iPhone, which will make the technology available-at least on a rudimentary level-to a growing portion of the population [4]. As computers become cheaper, we will soon find a day when advanced

[6]Auto-Tune is designed to transparently correct pitch, but with certain parameter settings can produce an artificial vocal sound, popular in much of today's music.

pitch correction can even be found in children's toys.

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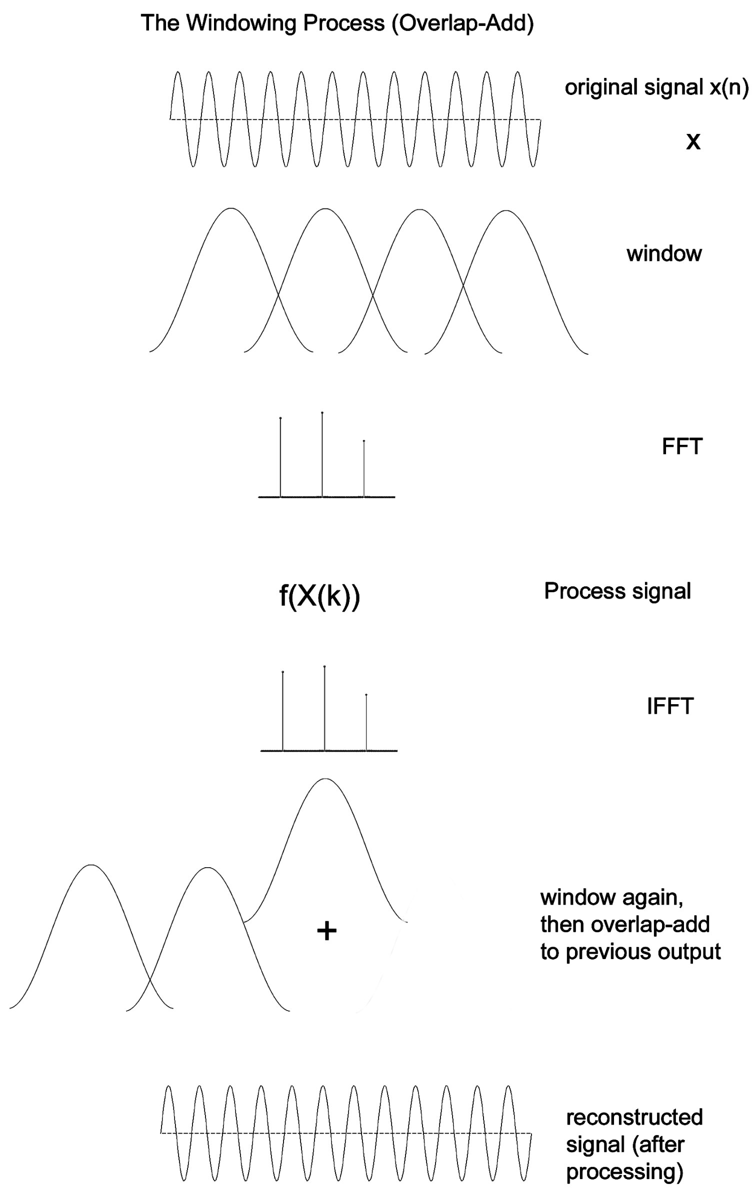
A Appendix: Additional Figures

Figure 12: A schematic of the Overlap and Add Windowing process.



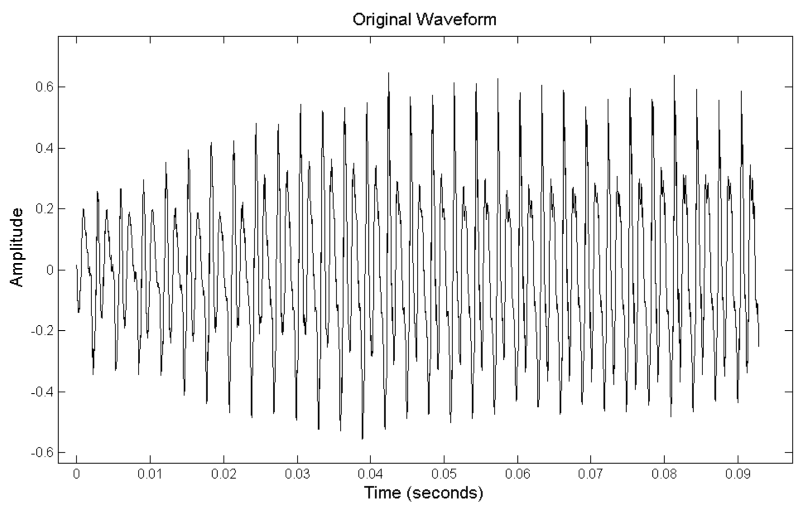


Figure 13: Original waveform used in HPS algorithm