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# DTMF signal sensing and reconstruction using $L_1$-minimization

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**ABSTRACT**

L1-minimization solves the minimum L1-norm solution to an underdetermined linear system. It has recently received much attention, mainly motivated by the new compressive sensing theory that shows that under certain conditions an L1-minimization solution is also the sparsest solution to that system. In this paper an L1 minimization algorithm is proposed for solution of Dual Tone Multiple Frequ-ency (DTMF) reconstruction problems. In the method of Compressive sensing, a raw signal or image can be regarded as a vector which can be represented as a linear combination of certain *basis functions*. The discrete cosine transform (DCT) has been used as the basis function in the proposed algorithm. This algorithm considers only 500 samples and reconstructs the original signals exactly without any distortion. The compressed DTMF signal is estimated using DTMF decoder with the help of Goertzel algorithm, the popularity of which lies in the small number of points at which the DFT is estimated. We compare with the existing algorithms such as FFT and Goertzel algorithms. The results show the effectiveness of the proposed algorithm.



## Introduction

It is claimed that the amount of data required to represent signals and images should be decreased by huge factors and then be restored the originals exactly. Conventional approaches for sampling signals or images follow Shannon's Sampling theorem which states that to avoid losing information when capturing a signal or image, the sampling rate must be at least twice the maximum frequency present in the signal.

In many applications, including digital image and video cameras, the Nyquist rate is so high that too many samples result, making compression a necessity prior to storage or transmission. In other applications, including imaging systems like medical scanners and radars and high-speed analog-to-digital converters, increasing the sampling rate is very expensive.

Compressed Sensing is a novel sensing or sampling paradigm that goes against the common wisdom in data acquisition. CS theory asserts that one can recover certain signals and images from far fewer samples or measurements than traditional methods use. It is a simple and efficient signal acquisition technique that collects a few measurements about the signal of interest and later uses optimization techniques for reconstructing the original signal from what appears to be an incomplete set of measurements. Accordingly, CS can be seen as a technique for sensing and compressing data simultaneously.

To make this possible, Compressed sensing relies on two principles:

(i) Sparse representation of the signal of interest in some basis, and

(ii) Incoherence between the sensing matrix and the representation basis, which pertains to the sensing modality sparsity expresses the idea that the "information rate" of a continuous time signal may be much smaller than suggested by its band-width, or that a discrete-time signal depends on a number of degrees of freedom which is comparably much smaller than its (finite) length. More precisely, CS exploits the fact that many natural signals are sparse or compressible in the sense that they have concise representations when expressed in the proper basis $\psi$.

Incoherence extends the duality between time and frequency and expresses the idea that objects having a sparse representation in $\psi$ must be spread out in the domain in which they are acquired, just as a Dirac or a spike in the time domain is spread out in the frequency domain. Put differently, incoherence says that unlike the signal of interest, the sampling/sensing waveforms have an extremely dense representation in $\psi$ .

### *Introduction to DTMF tones*

Dual-tone multi-frequency signaling (DTMF) is used for telecommunication signaling over analog telephone lines in the voice-frequency band between telephone handsets and other communications devices and the switching center. The version of DTMF that is used in push-button telephones for tone dialing is known as Touch-Tone. It is the basis for voice communications control and is widely used worldwide in modern telephony to dial numbers and configure switchboards. It is also used in systems such as in voice mail, electronic mail and telephone banking.

Prior to the development of DTMF, numbers were dialed on automated telephone systems by means of pulse dialing (*Dial Pulse* or DP in the U.S.) or loop disconnect (LD) signaling, which functions by rapidly disconnecting and reconnecting the calling party's telephone line, similar to flicking a light switch on and off. The repeated interruptions of the line, as the dial spins, sounds like a series of clicks.

Multi-frequency signaling (MF) is a group of signaling methods that use a mixture of two pure tone (pure sine wave) sounds. Various MF signaling protocols were devised by the Bell System and CCITT. Based on using MF by specialists to establish long-distance telephone calls, *Dual-tone multi-frequency* (DTMF) signaling was developed for the consumer to

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signal their own telephone-call's destination telephone number instead of talking to a telephone operator.

This paper organized as follows. Section-II describes the generation of DTMF tones briefly. Section –III is devoted to

Compressed sensing of DTMF signals and simulation results are given in section-IV. Finally the conclusions and future scope is given at the end.

**Generating DTMF Tones**

A DTMF signal consists of the sum of two sinusoids or tones with frequencies taken from two mutually exclusive groups called Low frequency group (LFG) and High frequency group (HFG) as shown in table 1.

**Table 1. DTMF signal frequencies**

| Low frequency group | High frequency group |
|---|---|
| 697 Hz | 1209 Hz |
| 770 Hz | 1336 Hz |
| 852 Hz | 1477Hz |
| 941 Hz | |

These frequencies were chosen to prevent any harmonics from being incorrectly detected by the receiver as some other DTMF frequency. Each pair of tones contains one frequency of the low group and one frequency of the high group and represents a unique symbol.

The frequencies allocated to the push-buttons of the telephone pad are shown in Fig 1.

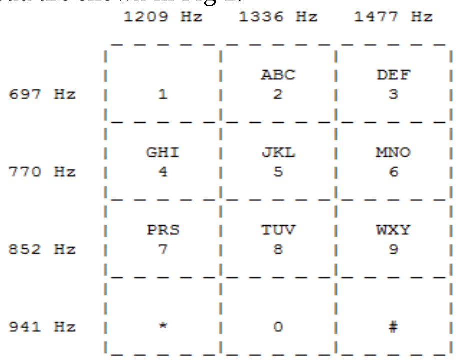



**Fig 1. Representation of telephone push button.**

From four frequencies of lower group and three frequencies of higher group, a total of twelve combinations are formed and thus represents twelve symbols; '1', '2', '3', '4', '5', '6', '7', '8', '9', '*', '0', '#'. Table.2 represents the corresponding frequencies of these symbols.

Therefore the DTMF signal for a particular tone is obtained by the sum of two sinusoids with corresponding frequency combinations and are shown in Table 3.

**Compressed Sensing of DTMF Signals**

Here it was proposed to use Discrete Cosine Transform (DCT) as basis function. Each of the DTMF signal generated by a key on the touch tone telephone pad are sampled at a Sampling frequency of 40000Hz for a period of 1/8 th of a second, that results a total of 5000 samples for each DTMF signal. Because the two frequencies of each DTMF tone are incommensurate, the signal does not fall exactly within the space spanned by the DCT basis functions, and so there are a few dozen significant nonzero coefficients.

In the sensing mechanism, sensing of a signal $f(t)$ generated by pressing of any key on the telephone pad, is defined as the process of collecting some measurements about $f(t)$ by correlating $f(t)$ with the mentioned sensing waveforms $\{\varphi_j(t)\}$, i.e., the basis function DCT.

**Table 2. Frequency combinations of different symbols**

| Symbol | Frequency combinations | |
|---|---|---|
| '1' | 697 | 1209 |
| '2' | 697 | 1336 |
| '3' | 697 | 1477 |
| '4' | 770 | 1209 |
| '5' | 770 | 1336 |
| '6' | 770 | 1477 |
| '7' | 852 | 1209 |
| '8' | 852 | 1336 |
| '9' | 852 | 1477 |
| '*' | 941 | 1209 |
| '0' | 941 | 1336 |
| '#' | 941 | 1477 |

**Table 3. DTMF signals for the frequency combinations of the 12 symbols**

| Symbol | DTMF tone |
|---|---|
| '1' | $f(t)=\sin(2\pi(697)t)+\sin(2\pi(1209)t)$ |
| '2' | $f(t)=\sin(2\pi(697)t)+\sin(2\pi(1336)t)$ |
| '3' | $f(t)=\sin(2\pi(697)t)+\sin(2\pi(1477)t)$ |
| '4' | $f(t)=\sin(2\pi(770)t)+\sin(2\pi(1209)t)$ |
| '5' | $f(t)=\sin(2\pi(770)t)+\sin(2\pi(1336)t)$ |
| '6' | $f(t)=\sin(2\pi(770)t)+\sin(2\pi(1477)t)$ |
| '7' | $f(t)=\sin(2\pi(852)t)+\sin(2\pi(1209)t)$ |
| '8' | $f(t)=\sin(2\pi(852)t)+\sin(2\pi(1336)t)$ |
| '9' | $f(t)=\sin(2\pi(852)t)+\sin(2\pi(1477)t)$ |
| '*' | $f(t)=\sin(2\pi(941)t)+\sin(2\pi(1209)t)$ |
| '0' | $f(t)=\sin(2\pi(941)t)+\sin(2\pi(1336)t)$ |
| '#' | $f(t)=\sin(2\pi(941)t)+\sin(2\pi(1477)t)$ |

$$x_j = \langle y, \phi_j \rangle \quad \text{for } j = 1, 2, \ldots, m$$

That is, we simply correlate the object we wish to acquire with the waveforms $\varphi_j(t)$. Fig 2 shows The random samples of the signal generated by a single key "A" and its inverse DCT.

Let 'A' denote the $m\times n$ sensing matrix with the vectors $\varphi_1, \varphi_2, \ldots \varphi_m$ as rows, the process of recovering $f \in R^n$ from $y = Af \in R^m$ is ill-posed in general when $m < n$, i.e there are infinitely many candidate signals f' for which A f' = y.

Accordingly, the equation for $x_j$ can be rewritten in matrix form as

$$x = \Phi y$$

where the jth row of the sensing matrix $\Phi \in R^{m\times n}$ is the discrete representation of the jth sensing function $\varphi_j(t)$, and $y \in R^n$ is the discrete representation of y(t).

For a single tone, the matrix A can be constructed by extracting m rows from the *n*-by-*n* DCT matrix

$$D = dct(eye(n,n));$$

$$A = D(k,:)$$

where k is the vector of indices used for the sample b. The resulting linear system, Ax = b, is m-by-n, which is 500-by-5000. There are 10 times as many unknowns as equations. To reconstruct the signal, we need to find the solution to Ax = b that minimizes the L1 norm of x. This is a nonlinear optimization problem, and one of the several MATLAB based programs, chosen to solve it is *L1-magic*, written by Justin Romberg and Emmanuel Candès.

The upper plot in Fig 3 shows the resulting solution, x. It is observed that it has relatively few large components and that it closely resembles the DCT of the original signal. Moreover, the discrete cosine transform of x, shown in the lower plot, closely resembles the original signal. If audio was available, it would be possible to hear that the two commands sound(f) and sound(dct($x$)) are nearly the same.

The process is repeated for all the keys on the telephone pad which results the similar reconstruction of the original tone signal. The Goertzel algorithm is well suited for this reconstruction of all the dual tone frequencies. Fig 3 shows the estimated DTMF tones in a telephone pad with The Goertzel algorithm.

**Simulation Results**

The concept of compressive sensing is first applied to a single tone frequency and is simulated for intermediate results on MATLAB software. The corresponding simulation results for sampled signal and its reconstructed signal for that single tone are shown in Fig 2 and Fig 3 respectively.

The similar approach of a single tone is applied to the group of DTMF signal, where the reconstructed signals are estimated using Goertzel algorithm. The corresponding results for sampled signal and its estimation are shown in Fig 4 and Fig 5 respectively.

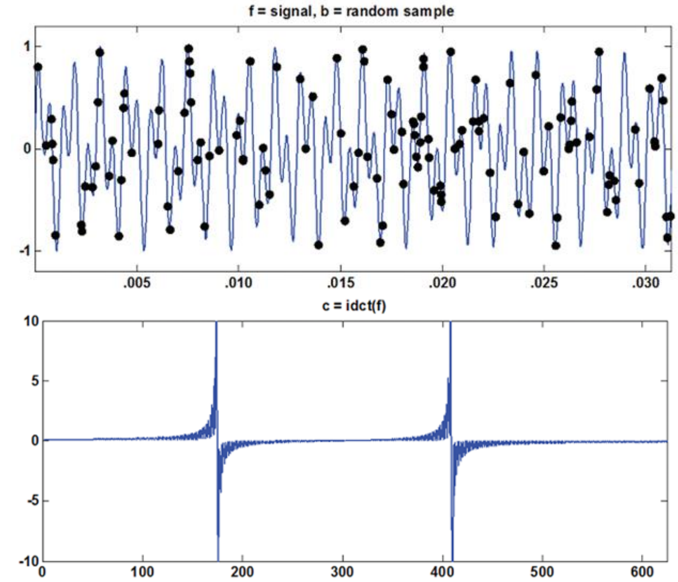
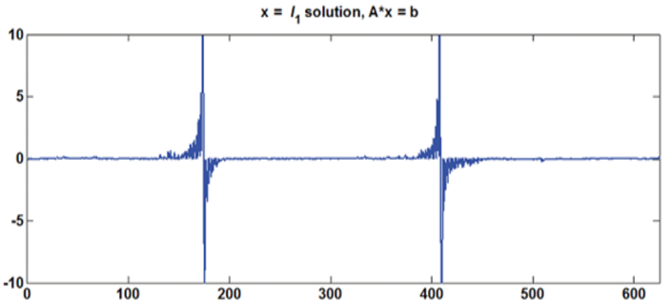



**Fig 1. The random samples of the signal generated by a single key "A" and its Inverse DCT**



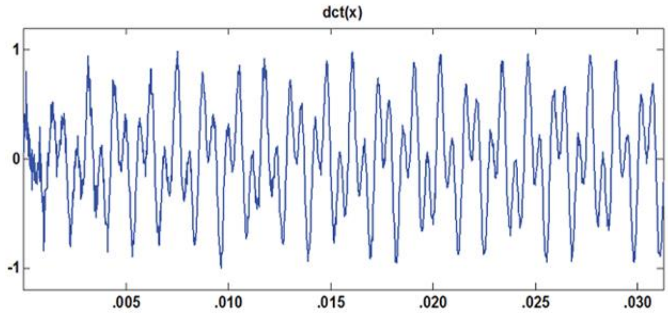




**Fig 2. The L1 solution to a single tone signal that is nearly equal to the original**

## Conclusion & Scope of Improvement

### *Conclusions*

The mechanism of Compressive sensing, as is well known, reduces the number of measurements for representing a signal and makes the system underdetermined. While reconstructing the original signal from these less number of measurements, they should preserve the originality of the signal. In this point of view, using L1 minimization algorithms is the best choice compared to L2 minimization. The L1 computation is practical because it can be posed as a linear programming problem and solved with the traditional simplex algorithm or modern interior point methods.

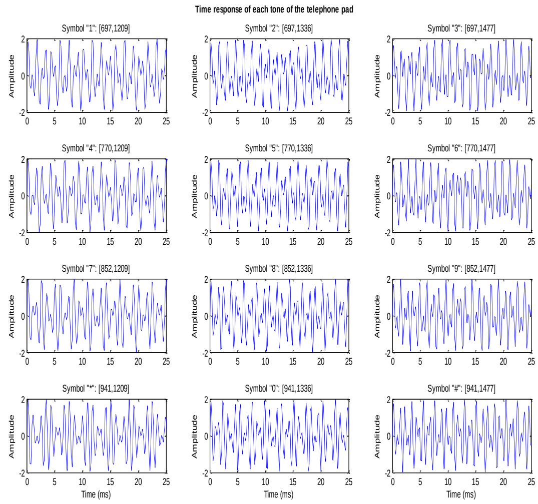



**Fig 3. Estimated DTMF tones in a telephone pad with Goertzel algorithm**

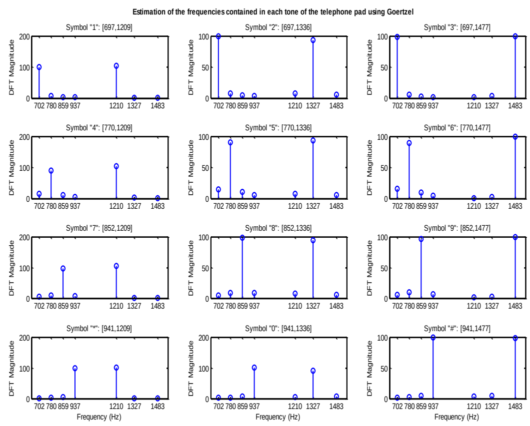



**Fig 4. Estimation of corresponding frequencies of each DTMF tone using Goertzel algorithm**

***Scope of Improvement***

Compressed sensing provides wider scope for improvement by sensing and compression of a signal of interest of any application. Here a DTMF signal is taken which is the basis for voice communication, but the similar concept can be applied to any type of signals where compression makes it efficient.

The DCT basis function was worked out effectively in our concept for compressing and reconstructing the signal. For better representation with fewer computations, one can work with Wavelet Transform.

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