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A Model for Suppresion of Mixed Gaussian-Impulse Noise In VOIP Systems

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Abstract: ***In this paper, we propose a robust time-frequency decomposition (RTFD) model to suppress of impulse noise mixed with small dense Gaussian noise in VoIP systems. Mixed Gaussian-impulse noise may appear during transmission over cordless phones, in VoIP systems and during the acquisition stage of old-time audio recordings. Voice over IP (VoIP) is a methodology and group of technologies for the delivery of voice communications and multimedia sessions over Internet Protocol (IP) networks. The transmission mechanism uses the IP protocol with an IP address. Special equipment must be used to convert the analog signal into a digital one. VoIP systems employ session control and signaling protocols to control the signaling, set-up, and tear-down of calls. Noise is an interference with the quality of the signal. Noise can be caused by a variation in the signal, packet loss, reduction in the signal strength, or by having additional users on the system such as the Internet. For this we develop 2 algorithm fidelity-oriented algorithm and articulation oriented with RTFD model. By this technique we can remov the noise from the VoIP systems.***

Keywords: VoIP,RTFD,IP,Gaussian-ImpulseNoise.

I. INTRODUCTION

Audio signals are sound waves—longitudinal waves which travel through air, consisting of compressions and rarefactions. These audio signals are measured in bels or in decibels. Audio processing was necessary for early radio broadcasting, as there were many problems with studio to transmitter links. Degradations can be systematically introduced into the underlying signal during the acquisition, storage and transmission processes. With modern people’s growing demand for high quality audio data, it has become important to restore these degraded signals.

Audio signals can be classified as analog signal & digital signal. Analog" indicates something that is mathematically represented by a set of continuous values; for example, the analog clock uses constantly moving hands on a physical clock face, where moving the hands directly alters the information that clock is providing. Thus, an analog signal is one represented by a continuous stream of data, in this case along an electrical circuit in the form of voltage, current or charge changes (compare with dig Analog signal processing (ASP) then involves physically altering the continuous signal by changing the voltage or current or charge via various electrical means. A digital representation expresses the pressure wave-form as a sequence of symbols, usually binary numbers. This permits signal processing using digital circuits such as microprocessors and computers. Although such a conversion can be prone to loss, most modern audio systems use this approach as the techniques of digital signal processing are much more powerful and efficient than analog domain signal processing. Processing methods and application areas include storage, level compression, data compression, transmission, enhancement (e.g., equalization, filtering, noise cancellation, echo or reverb removal or addition, etc.)

II. ESTIMATION OF NOISE

Different Types Of Noise

Some basic types of noise include Gaussian noise (like the electrical noise) and impulse noise (like short-time clicks).Mixed Gaussian-impulse noise may appear during transmission over cordless phones, in VoIP systems and during the acquisition stage of old-time audio recordings. As the most fundamental source of audio noise, additive Gaussian noise (AGN), which is usually introduced during the signal acquisition stage, is characterized by adding to each sample a value drawn from a zero-mean Gaussian distribution.Gaussian noise is usually relatively small in amplitude due to its mechanism of production. In early implementations, a spectral subtraction approach was widely used to suppress Gaussian noise. This approach estimates the power spectral density (PSD) of a clean signal by subtracting the PSD of Gaussian noise from the PSD of the noisy signal . The estimation of PSD is performed within short time segments,because the short-time spectral amplitude carries important information about both speech quality and intelligibility. In authors proposed a nonlocal means approach, which was originally developed for denoising natural images, to remove Gaussian noise in audio signals. Algorithms using statistical characteristics of speech signals were proposed in which models the noisy speech with a Laplacian-Gaussian mixture.As aforementioned denoising strategies focus on coping with Gaussian noise, it should not be ignored that many degraded audio signals also involve long-tailed noise processes, resulting often from faulty sensors and transmission errors . Such longtailed processes will introduce sparse outliers (or impulse noise) that can be arbitrarily large into audio data besides Gaussian noise. The performance of conventional restoration algorithms,which are particularly designed for noise of Gaussian type, will be highly degraded by such noise processes. Therefore, robust audio denoising algorithms that can suppress mixed Gaussian impulse noise are urgently needed. Existing impulse removal algorithms generally adopt two strategies, i.e. the detecting and replacing (DAR) strategy and the relaxing strategy.

Fidelity-Oriented Restoration

The DAR strategy mainly contains two stages, i.e. the detecting stage and the replacing stage. In the detecting stage, algorithms are designed to find noise corrupted samples; in the replacing stage corrupted samples are updated by approximate values estimated from reliable samples. Specifically, there are mainly two classes of impulse detecting algorithms, i.e. the statistical model based (SMB) algorithms and the threshold based (TB) algorithms. In SMB algorithms both the noise process and clean speeches are assumed to obey certain probability distributions [7], [8]. Then Bayes' rule is applied to obtain the posterior distribution of noise locations, and the final detecting results are given by the well-known MAP estimator. Quite differently, TB algorithms consider the discontinuous nature of noise corrupted waveforms [9], [10]. By comparing the sample amplitude (or its differential version) with a well-tuned threshold, TB algorithms algorithms regard the exceeded samples as being corrupted by impulse noise. The replacing algorithms also fall into two categories, i.e. the autoregressive (AR) modeling algorithm and sparse modeling algorithms. In the AR modeling approach, estimates of original samples are obtained by minimizing sum of squares of the residual errors that involve estimates of the AR parameters [11],[12]. On the other hand, sparse modeling algorithms generally utilize the frequency-domain sparsity especially in the voiced part [13]

In detail, the corrupted audio data should be expressed as:

$$s(t) = u(t) + n(t) + i(t)a(t), t = 1, 2, \ldots, L. \qquad (1)$$

Above L is the frame length; $s(t)$ represents the degraded signal; $u(t)$ is the underlying signal; $n(t)$ denotes Gaussian noise; $a(t)$ denotes the impulse noise amplitude; $i(t)$ is an impulse indicator defined as

$$i(t) = \begin{cases} 1 & \text{if sample } u(t) \text{ is corrupted by impulse noise} \\ 0 & \text{otherwise} \end{cases}. \qquad (2)$$

C. *Articulation-Oriented Restoration*

The relaxing strategy, on the other hand, does not attempt to detect outliers, since it seems impossible especially when the noise proportion is relatively high. The word "*relaxing*" means such algorithms suppress impulse noise at the cost of disturbing all the data points. Since this compromise will result in slight change on clean samples, which is undesirable, such a strategy is referred to as the relaxing strategy. In consideration of aforementioned reasons, the relaxing strategy attempts to remove impulsive samples in an overall manner. Typical algorithms include nonlinear filters such as median filters (MF), weighted median filters (WMF) and myriad filters [2]. Theoretically MF and WMF are optimal filters for constant signals contaminated by noise obeying a Laplace distribution. Myriad filters can be obtained if we assume noise amplitude obeys the Cauchy distribution

$$f(\xi|\xi_0, \vartheta) = \frac{1}{\pi}\left[\frac{\vartheta}{(\xi - \xi_0)^2 + \vartheta^2}\right] \qquad (3)$$

III. ALGORITHM DEVELOPMENT

In this section we present our algorithms to suppress mixed Gaussian-impulse noise. We propose two algorithms based on DOMP, i.e. a fidelity-oriented detecting and replacing (FoDAR) algorithm and an articulation-oriented relaxing (AoR) algorithm. To distinguish proposed algorithms from conventional ones, we abbreviate them as the FoDAR-DOMP and AoR-DOMP algorithm. Conventional FoDAR algorithms using OMP, BP and ARmodel are abbreviated as FoDAR-OMP,FoDAR-

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BP and FoDAR-AR, respectively. Conventional AoR algorithms using OMP and BP are abbreviated as AoR-OMP and AoR-BP, respectively.

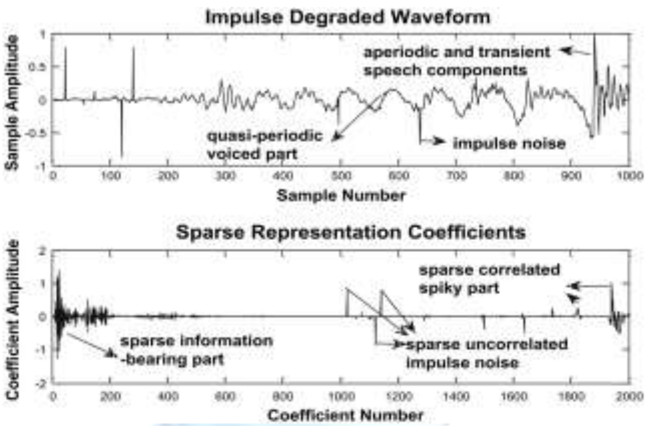

Fig.1

The proposed RTFD model lays the foundation of our restoration framework. The noise corrupted speech can be decomposed

$$\mathbf{s} = \mathbf{s}_1 + \mathbf{y}_1 + \mathbf{y}_2 + \mathbf{n}. \quad (4)$$

s_1,y_1,y_2 and n denote the quasi-periodic and voiced part, the aperiodic and transient part, the sparse uncorrelated impulse noise and the small dense Gaussian noise, respectively. We have labeled s_1,y_1,and y_2 at the top of Fig.1 Clean speeches are represented by s_1+y_1. Some useful properties of these parts should be noticed. For example,s_1 accounting for the most energy of clean speeches contains only a few large frequencies
and hence presents sparsity in the frequency domain.y_1 is associated with consonants, transitions between consonants and vowels, and transitions within some vowels. Besides,y_1 tends to present block-sparsity in the time domain.y_2 is also sparse in the time domain. White Gaussian noise is usually small in amplitude.s_1 and y_1+y_2 (denoted as s_2) are generally heterogeneous and possess different sparsity degrees.

IV. PROPOSED METHOD

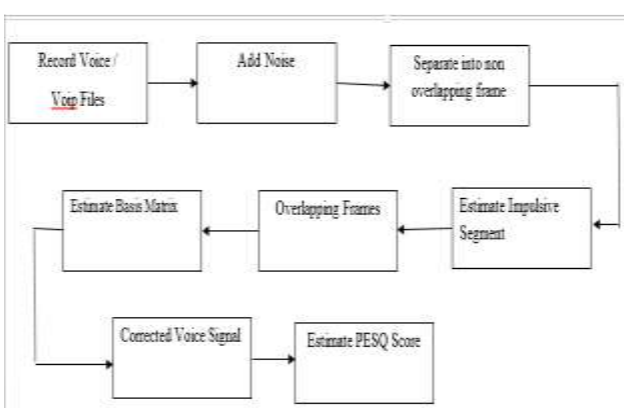

Fig .2 Architecture

This is simple architecture of project. Noise reduction is the process of removing noise from a signal. All recording devices, both analog and digital, have traits that make them susceptible to noise. Noise can be random or white noise with no coherence, or coherent noise introduced by the device's mechanism or processing algorithms

V. RESULTS

In this paper we mainly focus on removing impulse noise in the presence of small dense Gaussian noise in VoIP systems. We propose the RTFD model to represent degraded speeches. Then we develop the DOMP algorithm to more precisely solve the RTFD model.In the DOMP algorithm, we group the whole atom set into two subsets according to the generating process of observed audio signals. Based on RTFD and DOMP we have developed two restoration algorithms, i.e. FoDAR DOMP and AoR-DOMP. The former is suitable for slight impulse noise and the latter is suitable for heavy impulse.

Fig.3 Input Voice

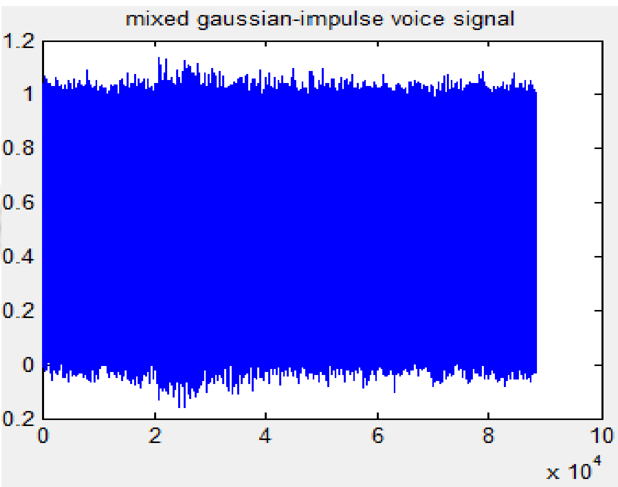

Fig.4 Noise Signal

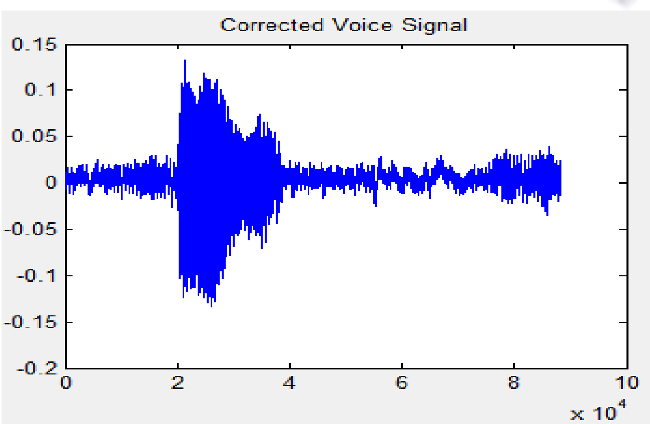

Fig.5 Corrected Signal

ABLE.1 PESQ SCORE

Algorithm Name	AR	BP	OMP	DOMP (μ=0.6)	DOMP (μ=0.8)	DOMP (μ=1.2)
p=0.5%	3.25	3.34	3.26	3.32	3.30	3.24
p=5%	2.64	2.57	2.46	2.41	2.42	2.43

VI. CONCLUSION

In this paper we develop a RTFD model for the suppression of Gaussion and Impulse noise. By this model we can get an application for the removal of noise in VoIP system. VoIP is a technology for the delivery of voice communication. Normaly we use PSTN network for communication.We design a denoising application in sound processing. By this project we reduce noise in internet calling.

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