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Editors

  

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Advanced Computing, Networking and Informatics – Volume 1

Advanced Computing and Informatics
Proceedings of the Second International Conference on Advanced Computing, Networking and Informatics (ICACNI-2014)

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Foreword

The present volume is an outcome, in the form of proceedings, of the 2nd International Conference on Advanced Computing, Networking and Informatics, St. Thomas' College of Engineering and Technology, Kolkata, India, June 24–26, 2014. As the name of the conference implies, the articles included herein cover a wide span of disciplines ranging, say, from pattern recognition, machine learning, image processing, data mining and knowledge discovery, soft computing, distributed computing, cloud computing, parallel and distributed networks, optical communication, wireless sensor networks, routing protocol and architecture to data privacy preserving, cryptology and data security, and internet computing. Each discipline, itself, has its own challenging problems and issues. Some of them are relatively more matured and advanced in theories with several proven application domains, while others fall in recent thrust areas. Interestingly, there are several articles, as expected, on symbiotic integration of more than one discipline, e.g., in designing intelligent networking and computing systems such as forest fire detection using wireless sensor network, minimizing call routing cost with assigned cell in wireless network, network intrusion detection system, determining load balancing strategy in cloud computing, and side lobe reduction and beam-width control, where the significance of pattern recognition, evolutionary strategy and soft computing has been demonstrated. This kind of interdisciplinary research is likely to grow significantly, and has strong promise in solving real life challenging problems.

The proceedings are logically split in two homogeneous volumes, namely, Advanced Computing and Informatics (vol. 1) and Wireless Networks and Security (vol. 2) with 81 and 67 articles respectively. The volumes fairly represent a state-of-the art of the research mostly being carried out in India in these domains, and are valued-additions to the current era of computing and knowledge mining.

The conference committee, editors, and the publisher deserve congratulations for organizing the event (ICACNI-2014) which is very timely, and bringing out the archival volumes nicely as its output.

Kolkata, April 2014

Sankar K. Pal
Distinguished Scientist and former Director
Indian Statistical Institute

Message from the Honorary General Chair

It gives me great pleasure to introduce the *International Conference on Advanced Computing, Networking and Informatics (ICACNI 2014)* which will be held at St. Thomas' College of Engineering and Technology, Kolkata during June 24–26, 2014. ICACNI is just going to cross its second year, and during this small interval of time it has attracted a large audience. The conference received over 650 submissions of which only 148 papers have been accepted for presentation. I am glad to note that ICACNI involved top researchers from 26 different countries as advisory board members, program committee members and reviewers. It also received papers from 10 different countries.

ICACNI offers an interesting forum for researchers of three apparently diverse disciplines: Advanced Computing, Networking and Informatics, and attempts to focus on engineering applications, covering security, cognitive radio, human-computer interfacing among many others that greatly rely on these cross-disciplinary research outcomes. The accepted papers are categorized into two volumes, of which volume 1 includes all papers on advanced computing and informatics, while volume 2 includes accepted papers on wireless network and security. The volumes will be published by Springer-Verlag.

The conference includes plenary lecture, key-note address and four invited sessions by eminent scientists from top Indian and foreign research/academic institutes. The lectures by these eminent scientists will provide an ideal platform for dissemination of knowledge among researchers, students and practitioners. I take this opportunity to thank all the participants, including the keynote, plenary and invited speakers, reviewers, and the members of different committees in making the event a grand success.

Thanks are also due to the various Universities/Institutes for their active support towards this endeavor, and lastly Springer-Verlag for publishing the proceedings under their prestigious *Smart Innovation, Systems and Technologies (SIST) series*.

Wish the participants an enjoyable and productive stay in Kolkata.

Kolkata, April 2014

Dwijesh Dutta Majumder
Honorary General Chair
ICACNI -2014

Preface

The twenty first century has witnessed a paradigm shift in three major disciplines of knowledge: 1) Advanced/Innovative computing ii) Networking and wireless Communications and iii) informatics. While the first two are complete in themselves by their titles, the last one covers several sub-disciplines involving geo-, bio-, medical and cognitive informatics among many others. Apparently, the above three disciplines of knowledge are complementary and mutually exclusive but their convergence is observed in many real world applications, encompassing cyber-security, internet banking, healthcare, sensor networks, cognitive radio, pervasive computing and many others.

The International Conference on *Advanced Computing, Networking and Informatics* (ICACNI) is aimed at examining the convergence of the above three modern disciplines through interactions among three groups of people. The first group comprises leading international researchers, who have established themselves in one of the above three thrust areas. The plenary, the keynote lecture and the invited talks are organized to disseminate the knowledge of these academic experts among young researchers/practitioners of the respective domain. The invited talks are also expected to inspire young researchers to initiate/orient their research in respective fields. The second group of people comprises Ph.D./research students, working in the cross-disciplinary areas, who might be benefited from the first group and at the same time may help creating interest in the cross-disciplinary research areas among the academic community, including young teachers and practitioners. Lastly, the group comprising undergraduate and master students would be able to test the feasibility of their research through feedback of their oral presentations.

ICACNI is just passing its second birthday. Since its inception, it has attracted a wide audience. This year, for example, the program committee of ICACNI received as many as 646 papers. The acceptance rate is intentionally kept very low to ensure a quality publication by Springer. This year, the program committee accepted only 148 papers from these 646 submitted papers. An accepted paper has essentially received very good recommendation by at least two experts in the respective field.

To maintain a high standard of ICACNI, researchers from top international research laboratories/universities have been included in both the advisory committee and the program committee. The presence of these great personalities has helped the conference to develop its publicity during its infancy and promote it quality through an academic exchange among top researchers and scientific communities.

The conference includes one plenary session, one keynote address and four invited speech sessions. It also includes 3 special sessions and 21 general sessions (altogether 24 sessions) with a structure of 4 parallel sessions over 3 days. To maintain good question-answering sessions and highlight new research results arriving from the sessions, we selected subject experts from specialized domains as session chairs for the conference. ICACNI also involved several persons to nicely organize registration, take care of finance, hospitality of the authors/audience and other supports. To have a closer interaction among the people of the organizing committee, all members of the organizing committee have been selected from St. Thomas' College of Engineering and Technology.

The papers that passed the screening process by at least two reviewers, well-formatted and nicely organized have been considered for publication in the Smart Innovations Systems Technology (SIST) series of Springer. The hard copy proceedings include two volumes, where the first volume is named as *Advanced Computing and Informatics* and the second volume is named as *Wireless Networks and Security*. The two volumes together contain 148 papers of around eight pages each (in Springer LNCS format) and thus the proceedings is expected to have an approximate length of 1184 pages.

The editors gratefully acknowledge the contribution of the authors and the entire program committee without whose active support the proceedings could hardly attain the present standards. They would like to thank the keynote speaker, the plenary speaker, the invited speakers and also the invited session chairs, the organizing chair along with the organizing committee and other delegates for extending their support in various forms to ICACNI-2014. The editors express their deep gratitude to the Honorary General Chair, the General Chair, the Advisory Chair and the Advisory board members for their help and support to ICACNI-2014. The editors are obliged to Prof. Lakhmi C. Jain, the academic series editor of the SIST series, Springer and Dr. Thomas Ditzinger, Senior Editor, Springer, Heidelberg for extending their co-operation in publishing the proceeding in the prestigious SIST series of Springer. They also like to mention the hard efforts of Mr. Indranil Dutta of the Machine Intelligence Unit of ISI Kolkata for the editorial support. The editors also acknowledge the technical support they received from the students of ISI, Kolkata and Jadavpur University and also the faculty of NIT Rourkela and St. Thomas' College of Engineering and Technology without which the work could not be completed in right time. Lastly, the editors thank Dr. Sailesh Mukhopadhyay, Prof. Gautam Banerjee and Dr. Subir Chowdhury of St. Thomas' College of Engineering and Technology for their support all the way long to make this conference a success.

Kolkata
April 14, 2014

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Application of Bilinear Recursive Least Square Algorithm for Initial Alignment of Strapdown Inertial Navigation System

Bidhan Malakar and B.K. Roy

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Abstract. To improve the alignment accuracy and convergence speed of Strapdown inertial navigation system, an initial alignment which is based on Bilinear Recursive Least Square adaptive filter is proposed. The error model for the Strapdown Inertial Navigation System (SINS) is derived from the dynamic model by considering a small misalignment angle. In the literature many algorithms are proposed for the proper estimation of alignment accuracy for INS and it is still a challenge. In this paper, two algorithms which are mainly based on nonlinear adaptive filter viz. Volterra Recursive Least Square (VRLS) and Bilinear Recursive Least Square (BRLS) are proposed and compared for proper estimation of accurate azimuth alignment error. The comparative performances of the aforesaid algorithms are studied and the performance of proposed BRLS algorithm is found to be effective which is obtained in existence of two different white Gaussian noises. The simulation work is done in MATLAB simulating environment. For the realization and validation of proposed BRLS algorithm, the comparative analysis is also precisely presented.

1 Introduction

The Strapdown Inertial Navigation System (SINS) [1] has special advantages and is widely being adopted for the accurate positioning and navigation of missiles, aeroplanes, ships, and railway vehicles etc. INS is advantageous when compared with (Global Positioning System) GPS, as it is unaffected by the external sources. However the INS output is subjective to the errors in the data which is supplied to the system during long durations and also can be due to inaccurate design and construction of the system components. Three types of errors are mainly responsible for the rate at which navigation error grow over long distances of time and these are the initial alignment errors, sensor errors and computational errors. The initial alignment [2-5] is the main key technology in SINS and depending upon the sensors configuration it must provide accurate result. The main purpose of initial alignment is to get the initial coordinate transformation matrix from the body frame to computer coordinates frame and the misalignment angle is considered to be zero during the mathematical modeling. The performance of inertial navigation system is affected by

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the alignment accuracy directly as well as initial alignment time which is mainly responsible for the rapid response capability. Therefore there is a requirement of shorter alignment time with a high precision in initial alignment.

At present, Kalman filtering [2] techniques are basically used in order to achieve the initial alignment of inertial navigation system due to its simplicity and also considered as an effective method. But in conventional Kalman filtering technique one must have the future knowledge of the mathematical models [6] and the noise statistics must also be studied and considered. In case of conventional Kalman filter, it is unable to provide a better and efficient result.

After introduction in section 1, section 2 briefly describes initial SINS alignment. The description of estimation algorithms are given in section 3. Section 4 deals with the dynamic modeling used for the simulation. Section 5 deals with the dynamic simulation of fine alignment. Section 6 presents the results, discussions and the comparison between the proposed algorithms. Finally, we conclude the paper in section 7.

2 SINS Initial Alignments

2.1 Coarse Alignment

An INS determines the position of the body frame by the integration of measured acceleration and rotation rate. Since the position is always relative to the starting position and for this reason the INS must know the position, attitude and heading before the navigation begins. The position is assumed to be known but the attitude and heading needs to be determined and is the process of alignment [7], [8].

In the coarse alignment stage the measured acceleration and rotation rate in body frame is compared with the gravity vector G along with the Earth's rotation rate and it directly estimates transformation matrix of carrier coordinates to geographical coordinates. It estimates the attitude and heading accurately enough to justify the small angle approximations made in the error model, and hence allow fine alignment to use an adaptive filter using the error model to obtain a more precise alignment which helps to determine the direction cosine matrix or attitude matrix C_n^b relating the navigation frame (n) and body frame (b). For determining the orientation of the body frame INS makes the use of the accelerometers and gyroscopes for measurement with respect to a reference frame and it is required for the estimation of the measured value of C_n^b .

The basic of alignment in SINS is discussed which plays an important role to improve the initial alignment. Many algorithms are being proposed recently in the literature for estimation and optimization of errors for SINS [9-11]. A theoretical background of the proposed algorithms is discussed in the next section.

3 Theoretical Background

The general set up of an adaptive-filtering [12] environment is illustrated in Fig. 1.

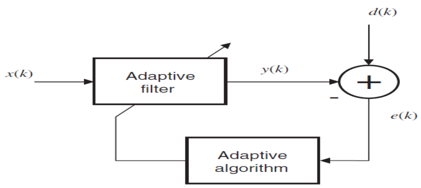

Fig. 1. Adaptive filtering structure

Here *k* is the iteration number, *x*(*k*) denotes the input signal, *y*(*k*) is the adaptive-filter output signal, and *d*(*k*) defines the desired signal [12]. The error signal *e*(*k*) is calculated as *d*(*k*)-*y*(*k*). In order to determine the proper updating of the filter coefficients, the error signal is then used to form a performance (or objective) function that is required by the adaptation algorithm. The minimization of the objective function implies that the adaptive-filter output signal is matching the desired signal in some sense.

3.1 Bilinear RLS Algorithm (BRLS)

The most widely accepted nonlinear difference equation model used for adaptive filtering is the so-called bilinear equation given by (1).

$$y(k) = \sum_{m=0}^{M} b_m(k)x(k-m) - \sum_{j=1}^{N} a_j(k)y(k-j) + \sum_{i=0}^{I}\sum_{l=1}^{L} C_i, lx(k-i)y(k-l) \quad (1)$$

Here *y*(*k*) is the adaptive-filter output and for this case, the signal information vector is defined by (2) and (3).

$$\phi(k)=\left[x(k)\ x(k-1)\dots\ x(k-M)\ y(k-1)\ y(k-2)\ y(k-N)\ x(k)y(k-1)\ x(k-I)y(k-L+1)\ x(k-I)y(k-L)\right]^T \quad (2)$$

$$\theta(k)=\left[b_0(k)\ b_1(k)\dots\ b_M(k)\ -a_1(k)\ -a_2(k)\dots\ -a_N(k)\ C_{0,1}(k)\ CI,L-1(k)\ CI,L(k)\right]^T \quad (3)$$

Here *N*, *M*, *I* and *L* are the orders of the adaptive-filter difference equations.

After the explanation of the two nonlinear adaptive algorithms that are used in the estimation of initial alignment angles error in SINS. The next section presents the dynamic model of SINS.

```
1. Initialization (set parameters for input vector
              initialization)
   ai(k)= bi(k)= ci,1(k)= e(k)=0.
   y(k)= x(k)= 0, k<0
   Sd(0)=δ^-1 I where δcan be the inverse of an estimate of
              the input signal power
   e(k) is the signal error
   Sd= inverse of the deterministic correlation matrix
              of the input vector
   I= identity matrix
2. For each x(k), d(k), k≥0, do
    y(k)= θ^T(k)θ(k)
    e(k)= d(k) - y(k)
    e(k)= signal error, y(k)=adaptive filter output,
    θ(k)= coefficient vector
3. Calculate e(k) using the relation
```

$$S_D(k+1)=\frac{1}{\lambda}[S_D(k)-\frac{S_D(k)\varphi(k)\varphi^T(k)S_D(k)}{\lambda+\varphi^T(k)S_D(k)\varphi(k)}]$$

$$\theta(k+1)=\theta(k)-S_D(k+1)\varphi(k)e(k)$$

4 Dynamic Modeling

The model of a local level NED (North-East-Down) [2] frame is used in this paper as the navigation frame. From the alignment point of view the East and North axes are referred to as leveling axes and “Down” axis are called the azimuth axis. The position and velocity errors are ignored. The state equations [2] can be represented as given.

$$\dot{X} = AX + FW = \begin{pmatrix} P_1 & P_2 \\ 0_{5X5} & 0_{5X5} \end{pmatrix} X + \begin{pmatrix} P_2 \\ 0_{5X5} \end{pmatrix} W \tag{4}$$

where $X = [\delta V_N \ \ \delta V_E \phi_N \phi_E \phi_D \nabla_x \nabla_y \varepsilon_x \varepsilon_y \varepsilon_z]^T$

$\delta V_N, \delta V_E$ are the east and north velocity error respectively and ∇_x, ∇_y for accelerometer error.

ϕ_N, ϕ_E are the two level milianment angles and ϕ_U for the misalignment angle.

$\varepsilon_x, \varepsilon_y, \varepsilon_z$ are the gyro error and ω_{ie} for the Earth rotation rate.

The observation equation for Initial alignment of SINS is given by,

$$Y = \mathrm{T}X + V \tag{5}$$

where, $Y = \begin{pmatrix} \delta V_E \\ \delta V_N \end{pmatrix}$, $\mathrm{T} = \begin{pmatrix} \mathrm{I}_{2X2} \\ 0_{2X8} \end{pmatrix}^T$ and V is the assumed to be the white noise.

The system noise is as follows,

$$W = [w_{ax} w_{ay} w_{gx} w_{gy} w_{gz}]^T$$

where x, y, z correspond to the Northeast coordinates (NED).

$$P_1 = \begin{pmatrix} 0 & 2\omega_{ie} Sin(L_0) & 0 & -g & 0 \\ -2\omega_{ie} Sin(L_0) & 0 & g & 0 & 0 \\ 0 & -\frac{1}{R} & 0 & \omega_{ie} Sin(L_0) & -\omega_{ie} Cos(L_0) \\ \frac{1}{R} & 0 & -\omega_{ie} Sin(L_0) & 0 & 0 \\ \frac{\tan L_0}{R} & 0 & \omega_{ie} Cos(L_0) & 0 & 0 \end{pmatrix}$$

and,

$$P_2 = \begin{pmatrix} C_{11} & C_{12} & 0 & 0 & 0 \\ C_{21} & C_{22} & 0 & 0 & 0 \\ 0 & 0 & C_{11} & C_{12} & C_{13} \\ 0 & 0 & C_{21} & C_{22} & C_{23} \\ 0 & 0 & C_{31} & C_{32} & C_{33} \end{pmatrix}$$

With the help of transformation matrix i.e. posture matrix P_2 the NED coordinate system can be transformed into body coordinate system and is given by,

$$P_2 = \begin{pmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{pmatrix}$$

$C_{11} = \cos(\phi_N)\cos(\phi_U) - \sin(\phi_E)\sin(\phi_N)\sin(\phi_U)$, $C_{12} = \sin(\phi_E)\sin(\phi_N)\cos(\phi_U) + \cos(\phi_N)\sin(\phi_U)$, $C_{13} = -\sin(\phi_N)\cos(\phi_E)$,
$C_{21} = -\cos(\phi_E)\sin(\phi_U)$, $C_{22} = \cos(\phi_E)\cos(\phi_U)$, $C_{23} = \sin(\phi_E)$,
$C_{31} = \sin(\phi_N)\cos(\phi_U) + \cos(\phi_N)\sin(\phi_E)\sin(\phi_U)$, $C_{32} = \sin(\phi_N)\sin(\phi_U) - \cos(\phi_N)\sin(\phi_E)\cos(\phi_U)$, $C_{33} = \cos(\phi_N)\cos(\phi_E)$

The systems observation equation by considering level velocity error as an external observation value is

$$Y = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} X + V \tag{6}$$

The continuous system in equation (4) and (5) must be converted into discrete system before the MATLAB simulation.

After modeling of the SINS the simulation of the model is given in the next section.

5 Dynamic Simulation of Fine Alignment

In order to evaluate the performance of the proposed Volterra RLS and Bilinear RLS algorithm, an example of a static self aligned stationary-base filtering program is considered, which use the NED coordinate frame [2]. The initial parameters used for the simulation are as follows.

Inertial navigation system location of longitude 125°, north latitude 45°, the initial value $\boldsymbol{X_0}$ of the state variable $\boldsymbol{X}$ are assigned to zero; P_0, Q and R are taken as the corresponding value of the middle-precision gyroscopes and accelerometers; and the initial misalignment $\delta V_N \delta V_E \phi_N \phi_E \phi_U \nabla_x \nabla_y \varepsilon_x \varepsilon_y \varepsilon_z$ angles ϕ_N ϕ_E ϕ_U are taken as $1°$; gyro drift are often taken as 0.02°/h, random drift taken as 0.01°/h; and accelerometers taken as 100µg, velocity errors taken as 0.1*m/s,* then

X_0 = diag{0,0,0,0,0,0,0,0,0,0}; P_0 = diag $[(0.1\ m/s)^2, (0.1\ m/s)^2, (1°)^2, (1°)^2, (1°)^2, (100\mu g)^2, (100\mu g)^2, (0.02°/h)^2, (0.02°/h)^2, (0.02°/h)^2]$; Q = diag $[(50\mu g)^2, (50\mu g)^2, (0.01°/h)^2, (0.01°/h)^2, (0.01°/h)^2, 0, 0, 0, 0, 0, 0]$; R = diag $[([(0.1\ m/s)^2, (0.1\ m/s)^2)]$

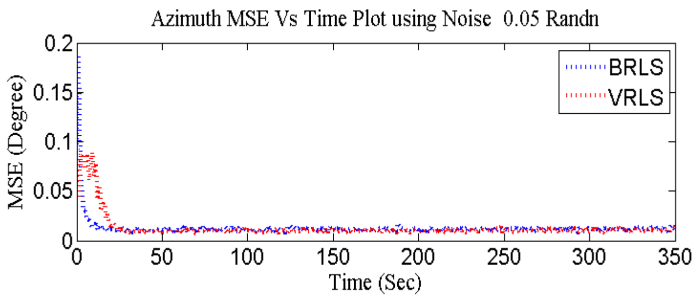

Fig. 2. Azimuth MSE plot vs time samples using BRLS and VRLS

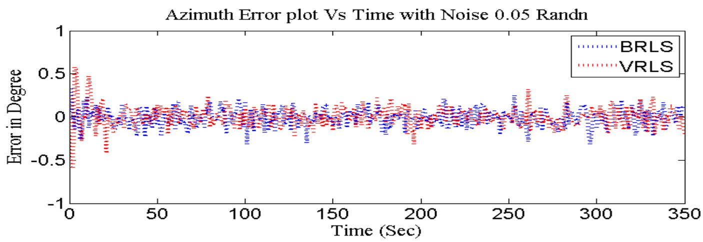

Fig. 3. Azimuth error plot vs time samples using BRLS and VRLS

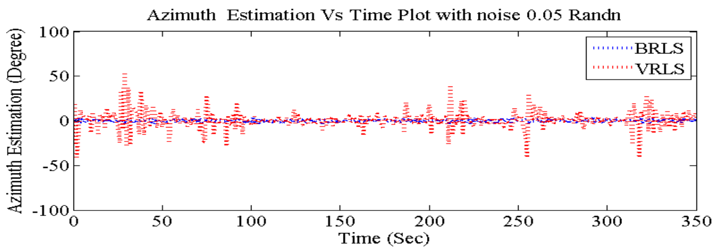

Fig. 4. Azimuth estimation plot vs time samples using BRLS and VRLS

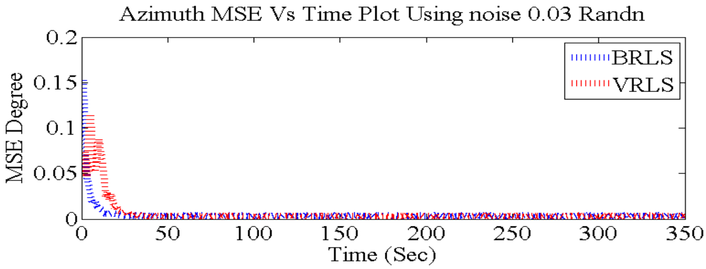

Fig. 5. Azimuth MSE plot vs time samples using BRLS and VRLS

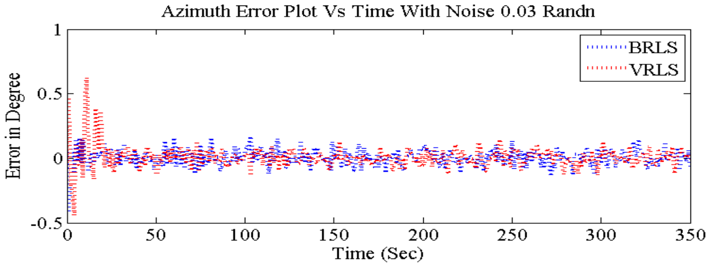

Fig. 6. Azimuth error plot vs time samples using BRLS and VRLS

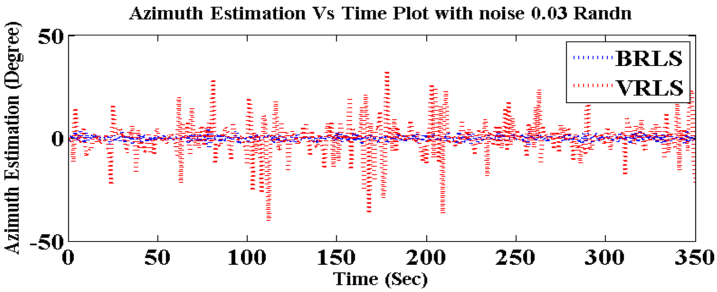

Fig. 7. Azimuth estimation plot vs time samples using BRLS and VRLS

In this section the various outputs obtained from the MATLAB on a laptop with 1GB RAM and 1.50 GHz processor, are shown and their performances characteristic are discussed in the next section.

6 Results and Discussions

The two algorithms are compared to each other by considering two different values of noises i.e. for 0.05 *rand*(*n*) and 0.03 *rand*(*n*). The performance of two algorithms for estimating Azimuth angle error is shown in Fig. 3, Fig. 6. Azimuth error estimation is shown in Fig. 4 and Fig. 7 and the MSE Azimuth angle error is shown in Fig. 2 and Fig. 5. The comparison performance is given in Table 1.

Table 1. Performance of The Proposed Algorithm for Estimating Azimuth angle Error

Algorithms	When Noise Covariance is 0.03	When Noise Covariance is 0.05	Computational Time (Sec)
VRLS	0.630	0.810	0.60624
BRLS	0.372	0.451	0.26374

7 Conclusions

This paper reports a research on the adaptive filtering technique applied to improve the estimation accuracy of SIN'S azimuth angle error. From the simulation result it is observed that the BRLS filtering algorithm is one of the better and also an effective algorithm for the initial alignment accuracy and convergence speed of strap down inertial navigation system.

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Time-Domain Solution of Transmission through Multi-modeled Obstacles for UWB Signals

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Abstract. In this work, the time-domain solution for transmission through multi-modeled obstacles has been presented. The transmission through dielectric wedge followed by a dielectric slab has been analyzed. The analytical time-domain transmission and reflection coefficients for transmission through the conductor-dielectric interface, considering oblique incidence, are given for both soft and hard polarizations. The exact frequency-domain formulation for transmitted field at the receiver has been simplified under the condition of low-loss assumption and converted to time-domain formulation using inverse Laplace transform. The time-domain results have been validated with the inverse fast Fourier transform (IFFT) of the corresponding exact frequency-domain results. Further the computational efficiency of both the methods is compared.

Keywords: Ultra wideband, Propagation model, Transmission, Frequency-domain, Time-domain.

1 Introduction

In recent years, research in ultra wideband (UWB) propagation through indoor scenario where non line of sight (NLOS) communication is more dominant, has received great attention because of unique properties of UWB communication like resilient to multipath phenomena, good resolution and low power density. In radio propagation of UWB signals, especially in NLOS communication in deep shadow regions, transmitted field component proves to be very significant [1, 2]. Considering the huge bandwidth (3.1-10.6 GHz) of UWB signals, it is more efficient to study UWB propagation directly in time-domain (TD) where all the frequencies are treated simultaneously [3, 4]. The TD solution of transmitted field through a dielectric slab was presented in [5]. A simplified TD model for UWB signals transmitting through a dielectric slab was presented in [6, 7]. The TD solutions for the reflection and transmission through a dielectric slab were presented in [8].

In this paper, we present an approximate TD solution for the field transmitted through multi-modeled obstacles under the low-loss assumption, for UWB signals. In other words, an accurate TD solution for modeling the transmission of UWB signals through multi-modeled obstacles is presented. Transmission model is called multi-

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modeled because the transmission is considered through multiple shaped obstacles like a wedge followed by a slab. The analytical TD transmission and reflection coefficients, for transmission through the conductor-dielectric interface, considering oblique incidence, are presented for both soft and hard polarizations. Through these TD formulations, the expression of the TD transmitted field is obtained. The TD results are validated against the IFFT [9, 10] of the corresponding exact frequency-domain (FD) results. At last, the computational efficiency of the two approaches is compared to emphasize the significance of the TD solutions presented.

The paper is organized as follows. In section 2, the propagation environment is presented. Section 3 presents the TD transmission and reflection coefficients and the TD formulations for the computation of the transmitted field component. In section 4, the aforementioned numerical TD results are calculated and validated against the numerical IFFT of the corresponding exact FD results and finally section 5 concludes the paper.

2 Propagation Environment

The propagation environment is shown in Fig. 1, where a single dielectric wedge is followed by a dielectric slab. The parameters $r_i, i = 1,2...,5$ are the distances traversed by the transmitted field through the structure from the transmitter (Tx) up to the receiver (Rx).

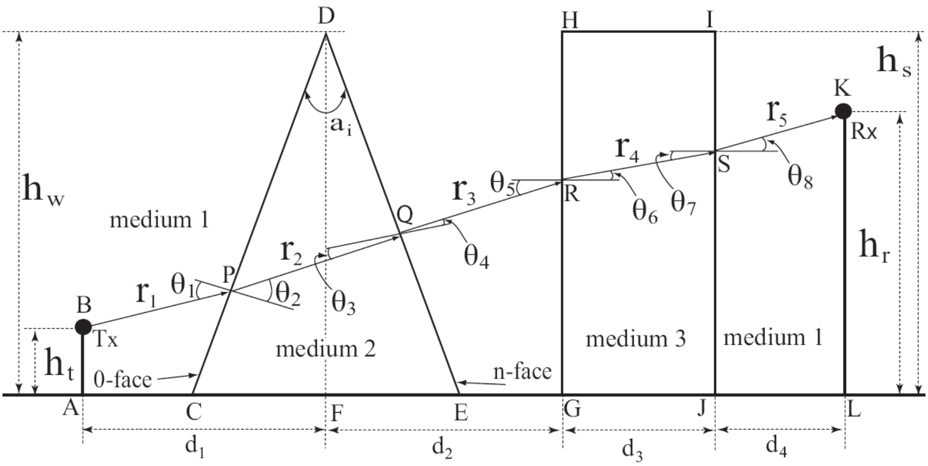

Fig. 1. Transmission through a dielectric wedge followed by a dielectric slab

Angles $\theta_1, \theta_3, \theta_5, \theta_7$ are the incidence angles with $\theta_2, \theta_4, \theta_6, \theta_8$ as the angles of refraction at points ‘P’, ‘Q’, ‘R’ and ‘S’ respectively and a_i is the internal wedge angle. The parameters h_t and h_r are the heights of the transmitter and the receiver, h_w is the height of the wedge and h_s is the height of the slab. Tx is at a distance d_1 from the wedge, d_2 is distance between wedge and slab, d_3 is width of slab and d_4 is distance between slab and Rx.

3 Proposed Transmission Model

3.1 TD Transmission Coefficient

The actual refracted angle across conductor-dielectric interface is given by [11]

$$\psi_t(\omega) = \tan^{-1}\{t(\omega)/q(\omega)\} \tag{1}$$

with $t(\omega) = \beta_1(\omega)\sin\theta_1$ and $q(\omega) = s(\omega)\{\alpha_2(\omega)\sin\zeta(\omega) + \beta_2(\omega)\cos\zeta(\omega)\}$.

where α_i and β_i are the attenuation constant and phase shift constant of i^{th} medium. θ_1 is the incident angle and $\cos\{\theta_2(\omega)\} = s(\omega)\exp[j\zeta(\omega)]$ with $\theta_2(\omega)$ as the complex refracted angle.

From (1) it is clear that the true refraction angle is also frequency dependent in nature, which means that for different frequency components of the UWB signal, the true real angles of refraction are different. However for low-loss dielectric obstacles (i.e. $\sigma/\omega\varepsilon << 1$), the different true refracted angles reduce to an effective, constant real angle [12]. Thus the real refracted angle ψ_t can be treated as constant and frequency independent, to obtain the approximate analytical TD transmission coefficients. Now for hard polarization case, transmission coefficient while propagating from conductor to dielectric medium, is given by [6, 13, 14]

$$\gamma_h(t) \approx \delta(t) - r_h(t) \tag{2}$$

$$r_h(t) = \left[K_h\delta(t)\right] + \frac{4k_h}{\left(1-k_h^2\right)}e^{-pt}\left[\frac{K_h}{2}X_h + \frac{(1-X_h)}{2K_h} - \frac{(pt)X_h}{4}\right] \tag{3}$$

with $X_h = e^{-\left(\frac{K_h pt}{2}\right)}$, $K_h = \left(\frac{1-k_h}{1+k_h}\right)$, $k_h = (\cos\theta_i/\cos\psi_t)(1/\sqrt{\varepsilon_{r2}})$, and $p = \tau/2$ with $\tau = \sigma/\varepsilon_2$.

where, ε_2 and εr_2 are dielectric permittivity and relative dielectric permittivity of the dielectric medium respectively. The TD transmission coefficient for a soft polarized wave propagating from conductor to dielectric medium is given as

$$\gamma_s(t) \approx \left[\delta(t) - r_s(t)\right]\left(\frac{\cos\theta_i}{\cos\psi_t}\right) \tag{4}$$

where, $r_s(t) = K_s\delta(t) + \frac{4k_s}{\left(1-k_s^2\right)}e^{-pt}\left[\frac{K_s}{2}X_s + \frac{(1-X_s)}{2K_s} - \frac{(pt)X_s}{4}\right]$ with

$X_s = e^{-\left(\frac{K_s pt}{2}\right)}$, $K_s = \left(\frac{1-k_s}{1+k_s}\right)$, $k_s = \left(\cos\psi_t/\cos\theta_i\right)\left(1/\sqrt{\varepsilon_{r2}}\right)$.

3.2 Transmitted Field through the Propagation Environment

The FD expression for the transmitted field at Rx through the structure shown in Fig. 1 is given by [2, 12]

$$E_{RX}(\omega) = \left(E_i(\omega)/r_{total}(\omega)\right)\left(\prod_{i=1}^{4} T_{i,s,h}(\omega)\right)\left(\exp(-jk_0 r_1)\prod_{j=2}^{5}\exp\left\{-\left(\alpha_{ej}(\omega)+j\beta_{ej}(\omega)\right)\right\}\right) \tag{5}$$

with $r_{total}(\omega) = \sum_{i=1}^{5} r_i$ and $T_{total,s,h}(\omega) = \prod_{i=1}^{4} T_{i,s,h}(\omega)$ where $T_{i,s,h}(\omega), i = 1,2...,4$ are the FD transmission coefficients with respect to points 'P', 'Q', 'R' and 'S' (See Fig. 1). $\alpha_{ej}(\omega), \beta_{ej}(\omega)$ are total effective attenuation constants and phase shift constants for different j^{th} regions [12]. Actual FD path-loss expression from (5) is given by

$$L_{total,s,h}(\omega) = \left(\exp(-jk_0 r_1)\prod_{j=2}^{5}\exp\left\{-\left(\alpha_{ej}(\omega)+j\beta_{ej}(\omega)\right)\right\}\right) \tag{6}$$

Now the corresponding TD expression for the received field at Rx based on the FD transmission model of [2] is as follows

$$e_{RX}(t) \approx \left(\frac{e_i(t)}{r_{total}}\right) * \Gamma_{1,s,h}(t) * \Gamma_{2,s,h}(t) * \Gamma_{3,s,h}(t) * \Gamma_{4,s,h}(t) * l_{total,s,h}(t) \tag{7}$$

with $'*'$ representing the convolution operator, $\Gamma_{1,s,h}(t) * \Gamma_{2,s,h}(t) * \Gamma_{3,s,h}(t) * \Gamma_{4,s,h}(t) = \Gamma_{total,s,h}(t)$ is the TD counterpart of $T_{total,s,h}(\omega)$, $l_{total,s,h}(t)$ [6, 7] is the TD counterpart of $L_{total,s,h}(\omega)$. The TD expressions for $\Gamma_{i,s,h}, i = 1,2...,4$ can be obtained using (2) and (4) for different polarizations.

For loss tangent much less than unity ($\sigma/\omega\varepsilon << 1$), the FD path-loss expression (6) reduces to the following approximate form with constant values of angles of refraction and along a single effective path for transmission:

$$L_{total,s,h}(\omega) \approx \exp\left(-jk_0(r_1+r_3+r_5)\right)\exp\left[-j\omega\sqrt{\mu\varepsilon}\left(1+\frac{\sigma}{2j\omega\varepsilon}\right)\left\{r_2+\left(d3\sqrt{\frac{\varepsilon_r}{\varepsilon_r-\sin^2\theta_5}}\right)\right\}\right] \tag{8}$$

Here $r_1+r_3+r_5$ is the total distance travelled by the field in free space. ε and σ are the parameters of the dielectric mediums in Fig. 1 (assuming same for wedge and slab). The term $l_{total,s,h}(t)$ in (7) is then given by

$$l_{total,s,h}(t) \approx \exp\left[-\sqrt{\mu/\varepsilon}\,\left(\sigma/2\right)\left\{r_2 + \left(d3\sqrt{\frac{\varepsilon_r}{\varepsilon_r - \sin^2\theta_5}}\right)\right\}\right]$$
$$\delta\left[t - \sqrt{\mu\varepsilon}\left\{r_2 + \left(d3\sqrt{\frac{\varepsilon_r}{\varepsilon_r - \sin^2\theta_5}}\right)\right\}\right] * \delta\left(t - \frac{r_1 + r_3 + r_5}{c}\right) \tag{9}$$

This approximated TD path-loss expression will be used in (7) to compute the TD transmitted field and the accuracy will be proved by the comparison of TD transmitted field with the IFFT of the exact FD results, as shown in next section.

4 Results and Discussions

In this section, our goal is to compare the proposed TD solution with conventional IFFT-FD method. Table 1 shows the electromagnetic properties of the considered materials.

Table 1. Electromagnetic properties of different dielectric materials

Material	Relative Permittivity	Conductivity (S/ m)
Wood[6]	2	0.01
Drywall[15]	2.4	0.004
Glass[15, 16]	6.7	0.001

Fig. 2 shows the transmitted field through the propagation environment discussed in section 2, for both hard and soft polarizations. The transmitted field at Rx suffers no distortion in shape in comparison to the shape of the excited UWB pulse. This is because of small magnitude of the loss tangent with respect to unity. However, the amplitude of the transmitted field is attenuated because of the transmission loss through the dielectric mediums.

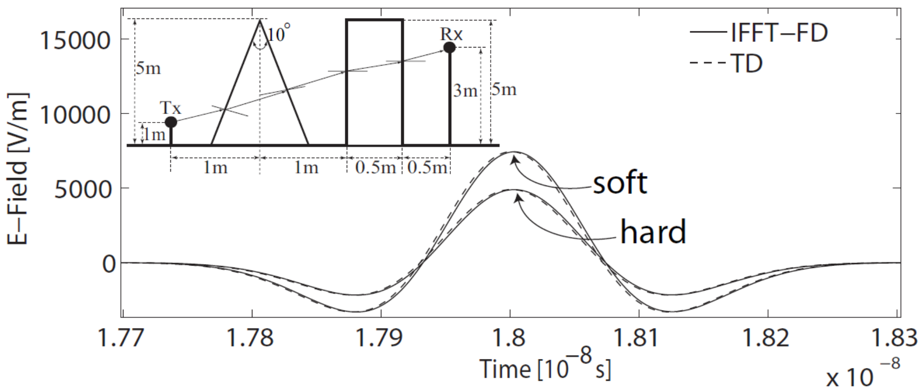

Fig. 2. Transmitted field through ‘dielectric wedge followed by a dielectric slab’, with glass [15, 16]

The TD results for the transmitted field for both the polarizations are in excellent agreement with corresponding IFFT of exact FD results, thus providing validation to the proposed TD solution.

Fig. 3 shows the effect of varying Rx position (changing distance d_4 in Fig. 1) on transmitted field at the receiver. Transmitted field gets more attenuated as Rx moves away from the obstacles. The results for soft and hard polarized fields come closer to each other as the distance d_4 increases. Also the TD results match closely with the IFFT-FD results.

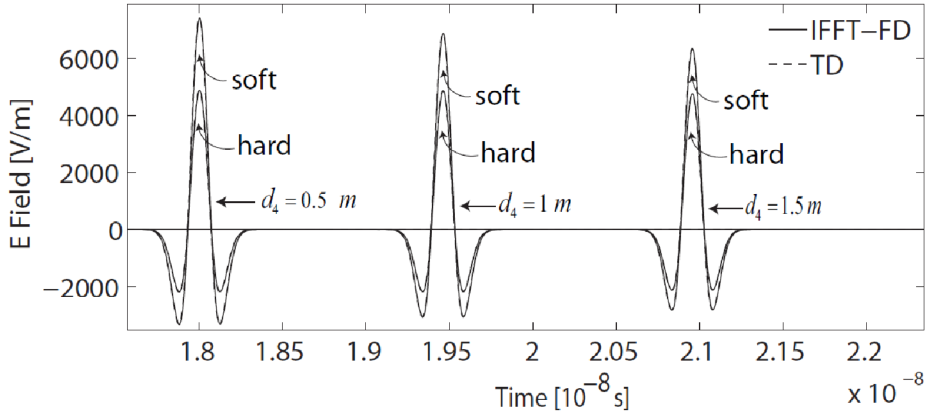

Fig. 3. Transmitted field through 'dielectric wedge followed by a dielectric slab' for different receiver positions, with glass [15, 16]

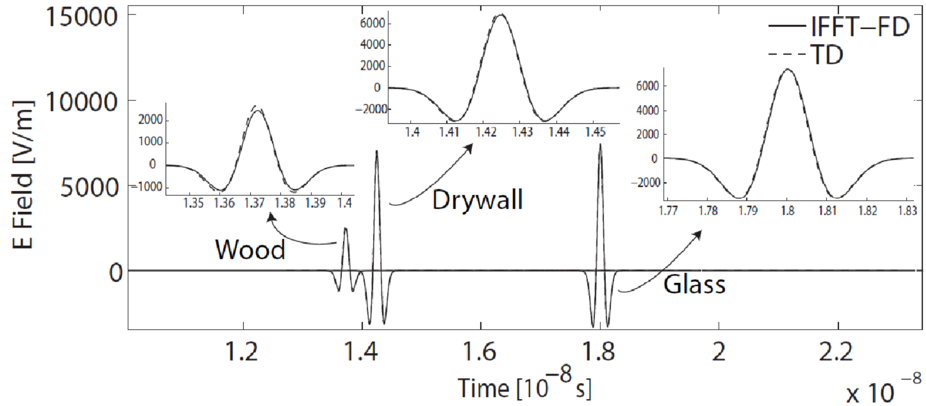

Fig. 4. Transmitted field through 'dielectric wedge followed by a dielectric slab' for different dielectric materials, with wood [6], drywall [15] and glass [15, 16]

Fig. 4 shows transmitted field at the receiver for different dielectric materials. The TD results are in good agreement with the IFFT-FD results. It can be seen that as the value of loss tangent decreases, a better agreement is achieved between the TD and IFFT-FD results.

A comparison between the computation times of the IFFT-FD method and the proposed TD solution for propagation profile considered in Fig. 1 is presented in Table 2. The presented results in Table 2 establish that the proposed TD analysis is computationally very efficient in comparison to the IFFT-FD solution.

Table 2. Efficiency comparison of two methods

Propagation profile	$T_{IFFT\text{-}FD}/T_{TD}$
For soft polarization	~198
For hard polarization	~191

The two main reasons for such a significant reduction in the computational time in TD are: (i) the efficient convolution technique [9] due to which few number of time samples suffice to provide accurate results. (ii) Approximation of the multiple transmission paths in FD by a single effective path for low-loss dielectric case.

Given the excellent agreement between proposed TD solution and IFFT of FD solution, it can be concluded that the proposed method is accurate for low loss tangent values in the UWB bandwidth. The presented work also establishes that the proposed TD solution is computationally more efficient than the conventional IFFT-FD method.

5 Conclusion

An analytical TD solution has been presented for the transmitted field through multi-modeled obstacles made up of low-loss dielectric materials. Analytical TD transmission and reflection coefficients for transmission through an interface between conductor and dielectric mediums are presented for soft and hard polarizations. The results of the proposed TD solution are validated against the corresponding IFFT-FD results and the computational efficiency of two methods is compared. The TD solution outperforms the IFFT-FD analysis in terms of the computational efficiency. The TD solution is vital in the analysis of UWB communication as it can provide a fast and accurate prediction of the total transmitted field in microcellular and indoor propagation scenarios.

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Indexing and Retrieval of Speech Documents

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Abstract. In this paper, a speech document indexing system and similarity-based document retrieval method has been proposed. K-d tree is used as the index structure and codebooks derived from speech documents present in the database, are used during retrieval of desired document. Each document is represented as a sequence of codebook indices. The longest common subsequence based approach is proposed for retrieving the documents. Proposed retrieval method is evaluated using a speech database of 3 hours recorded by a male speaker and speech queries from 5 male and 5 female speakers. The accuracy of retrieval is found to be about 88% for the queries given by male speakers.

Keywords: Indexing and Retrieval, codebook, MFCC, k-d tree, retrieval, longest common subsequence.

1 Introduction

Due to rapid advancement in technology, there has been explosive growth in the generation and use of multimedia data, such as video, audio, and images. A lot of audio and video data is generated by internet, mobile devices, TV and radio broadcast channels. Indexing systems are desirable for managing and supporting usage of large databases of multimedia. Audio indexing finds applications in digital libraries, entertainment industry, forensic laboratories and virtual reality.

Many kinds of indexing schemes have been developed, and studied by researchers working in this field [13]. An approach for indexing audio data is the use of text itself. Transcripts from the audio data are generated, which are used for indexing. This approach is effective for indexing broadcast news, video lectures, spoken documents, etc., where the clean speech data is available. The retrieval from such indexing system is performed using keywords as a query. For effective use of multimedia data, the users should be able to make content based queries or queries-by-example, which are unrestricted and unanticipated. Content based retrieval systems accept data type queries i.e., hummed, sung or original clip of a song for a song retrieval. The methods used for audio indexing can be broadly classified as under:

– Signal parameter based systems [1,3,9,14] - In this scheme, the signal statistics such as mean, variance, zero crossing rate, autocorrelation, histograms

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of samples/difference of samples, energy contour, loudness contour, etc. either on the whole audio signal data or blocks of data are used. This type of indexing supports query by example. Audio Fingerprinting [1] is an example of this type of system.
– Musical parameter based systems [2,7,8,10] - In this scheme, the parameters of signal along with acoustical attributes such as melody contour, rhythm, tempo, etc. extracted from the audio signal are used for indexing. This type of indexing scheme supports both query by example and query by humming. This method requires extensive calculations.

In the design of an audio indexing system following two aspects need to be addressed. (1). Derivation of good features from the audio data to be used as indices during search. (2). Organization of these indices in a suitable multidimensional data structure with efficient search. Selection of a good measure of similarity (distance measure). The objective of this work is to design a content-based speech indexing system which supports query by example. In this work, the features used for indexing purpose is a codebook derived from MFCC feature vectors for every 10 seconds of speech data present in the database. The k-d tree is used for providing the indexing structure [4] and longest common subsequence (LCS) [11], [5] has been used as a measurement for similarity for retrieval purpose.

Rest of the paper is organized as follows - Section II describes the framework of the proposed indexing and retrieval system. In Section III, experimental results and their analysis are discussed. The summary of the contents presented in the paper, and conclusions drawn from the observations are presented in Section IV.

2 Proposed Speech Indexing and Retrieval System

A speech file is a concatenated sequence of sounds. So finding a matching speech clip in the database to a query clip provided, can be thought of as finding the clip having the similar sounds in the same sequence. But since the query can be provided by any person, the two sequences will not be the exact duplicate of each other. This problem of matching the sequence of sounds can be mapped to the well known problem of determining the longest common subsequence from two sequences of characters. The only difference is that in place of characters there are sounds. By mapping the sound sequence matching problem to the longest common subsequence problem, a different issue arises. How do we map sounds to characters? Determining the longest common subsequence directly from the sounds of the speech files is very difficult because a speaker can produce many variants of a single sound. These variations increase tremendously with change in speaker. So we build codebooks to bring uniformity in these sound sequences. The process to derive a codebook is explained in Section 2.1.

The framework of the proposed speech indexing and retrieval system is shown in the Fig. 1. The tasks of the system and the challenges they pose, can be explained in three phases.

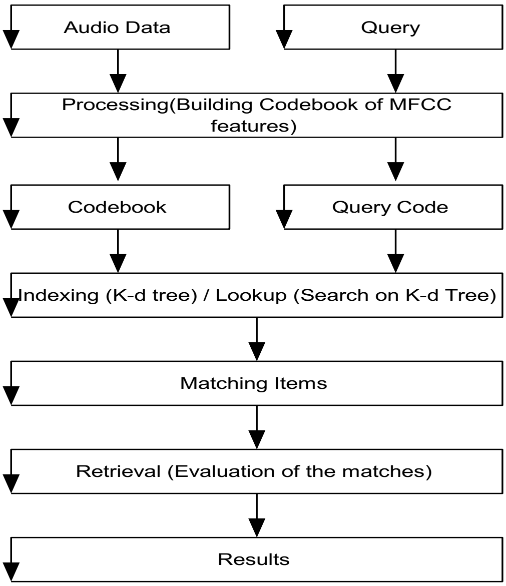

Fig. 1. Proposed speech indexing and retrieval system

Building the Codebook. Phase 1 (Preprocessing phase) converts all raw speech data into indexable items, typically, points in a high-dimensional vector space with an appropriate distance measure. In other words, in this phase we extract features from the speech files and the query to be processed. The features considered here are Mel-Frequency Cepstral Coefficients (MFCCs). MFCCs are determined from speech signal using the following steps:

1. Pre-emphasize the speech signal.
2. Divide the speech signal into sequence of frames with a frame size of 20 ms and a shift of 10 ms. Apply the Hamming window over each of the frames.
3. Compute magnitude spectrum for each windowed frame by applying DFT.
4. Mel spectrum is computed by passing the DFT signal through mel filter bank.
5. DCT is applied to the log mel frequency coefficients (log mel spectrum) to derive the desired MFCCs.

From each frame, 13 MFFCCs are extracted using 24 filter banks. This results in 1000 MFCC vectors for 10 seconds of speech. These 1000 vectors are then converted to a vector codebook using k-means clustering [12].

Fig. 2 shows the basic steps for building a vector quantization codebook and extraction of code book indices. Training data consists of 1000 MFCC vectors. The training data set is used to create an optimal set of codebook vectors for representing the spectral variability observed in the training data set. A centroid computation procedure is used as the basis of partitioning the training data set

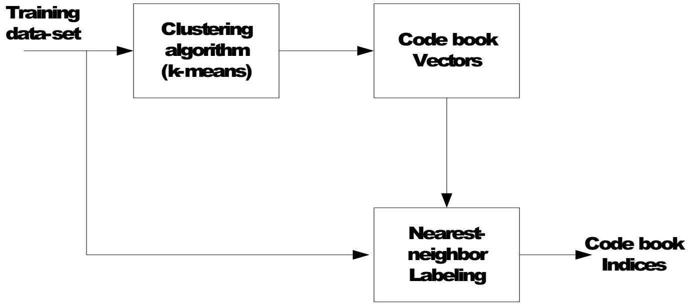

Fig. 2. Codebook building process and codebook indices extraction

into N clusters. Thus it forms an N-center codebook. Here, K-means clustering method is used for clustering the training data. Finally, nearest-neighbor labeling has been used to obtain a sequence of codebook indices. The size of codebook varies with the number of centers used for k-means clustering. The results shown in this paper have been generated on the codebook having 32 centers. A separate codebook is created for every 10 seconds of speech data in database.

Building the Index. Phase 2 (Indexing / Lookup phase) does the task of indexing the features extracted from the speech database. This phase also performs a lookup in the index to retrieve the best matching items for a query vector. The matching can be done in various ways, say, exact matching, nearest neighbour matching, etc. which depends on the application and the efficiency required.

In this work, MFCC feature vectors derived from speech consists of 13 dimensions. Various data structures can be used for multi-dimensional indexing, for example, quad tree, k-d tree, optimized k-d tree. In this work, the index is created from the codebook in the form of a k-d tree. The discriminating key for each level of the k-d tree is selected according to Bentleys definition of the k-d tree i.e., D = L *mod* k + 1, where D is the discriminating key number for level L and the root node is defined to be at level zero. However, the selection of the partition value is done in the way suggested by Friedman [4]. The partition value is selected as the median value in the dimension of the discriminator(D).

The codebooks created in this work have 32 codebook vectors. Each of these vectors is assigned an index number (1-32). This numbering of the codebook entries is utilized in Phase 3. We are required to preserve this numbering even when the codebook is converted to a k-d tree index. This is achieved by appending the index number as an additional dimension to the codebook vectors while creating the k-d tree. This 14th dimension is never used as a discriminating key while building the k-d tree index. The Algorithm 1 is used for k-d tree creation in this work.

The procedure *median(j,subfile)* returns median of the j^{th} key values. The procedures *make_terminal* and *make_non_terminal* store their parameters as values of the node in the k-d tree and return a pointer to that node. The $leftsubfile$ and $rightsubfile$ procedures, partition the file along the d^{th} key with respect

Algorithm 1. Algorithm used for k-d tree creation

Result: $root \leftarrow build\_tree(entirefile, 1)$

procedure $build\_tree(file, dim)$
    local p
    if $size(file) \leq b$ **then**
        return $(make\_terminal(file))$
    end
    $p \leftarrow median(dim, file)$
    $dim \leftarrow dim \text{ Mod } k + 1$
    $left \leftarrow build\_tree(left\_subfile(d, p, file))$
    $right \leftarrow build\_tree(right\_subfile(d, p, file))$
    return $make\_non\_terminal(d, p, left, right)$
end procedure

to the partition value p and return left and right subfiles, respectively. Heap-sort algorithm having complexity of *O(NlogN)*, is used to compute the median as well as the left and right sub file at each level. Thus the time complexity of building a k-d tree from N vectors is $O(Nlog^2N)$. The searching algorithm proposed by Friedman [4] is used in this work for searching the k-d tree. This search algorithm is also a part of Phase 2 of the system.

Evaluation of Matches. Phase 3 (Retrieval phase) evaluates all the matching items and decides which files among the database are the best candidates, to be returned as the query response. As mentioned earlier, in this work we use longest common subsequence determination technique for finding the matching speech fragments.

The sequence of codebook indices is generated by using the MFCC feature vector sequence of the speech clip. For each MFCC vector, the index number (1-32) of nearest codebook vector is determined by searching the k-d tree. These

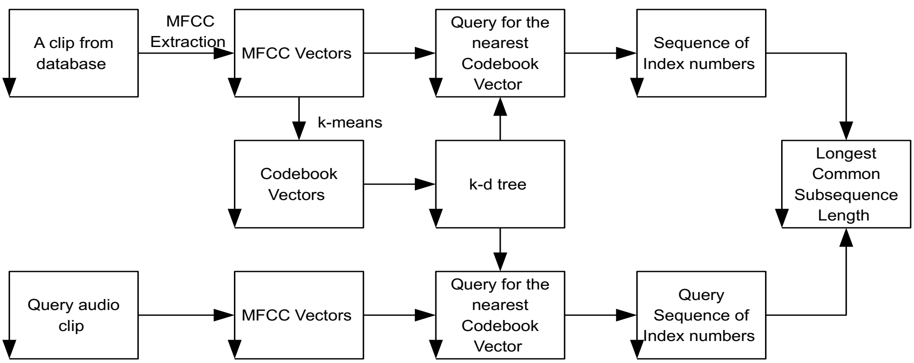

Fig. 3. Retrieval using longest common subsequence approach

index numbers are then concatenated to form a sequence of index numbers. The retrieval method finds out that clip in the database, whose MFCC vectors follow the similar codebook vector sequence, as that of the query clip. Steps in retrieval method are as follows:

1. After building the codebook for a speech document in the database, the MFCC vectors are scanned, in order of their occurrence, to determine the index number (1-32) of the nearest codebook vector.
2. By concatenating these index numbers obtained in the above step, we obtain an approximate sequence of sounds present in the clip.
3. MFCC vectors are extracted from the query speech clip provided.
4. By using the same technique of nearest neighbour search among the codebook vectors, we can obtain another sequence of index numbers. The length of the longest common subsequence between the sequences obtained in steps 2 and 4 is determined.
5. The length of the longest common subsequence obtained in step 4, can act as the similarity measure while comparison with other clips in the database, since the process of sequence determination will be repeated for all the clips in the database.

Longest Common subsequence is a classic problem in computer science. Many solutions are available in literature. In this work, longest common subsequence is determined by using dynamic programming technique (DP). DP is well known for its space efficient implementation and lower complexity. The entire process is summarized in Fig. 3.

3 Performance Evaluation

The database used for evaluation, consists of 3 hours of speech recorded by a single male speaker. The speech consists of articles about History of India available on Wikipedia. This recorded speech data was divided into 1080 speech documents, each of duration 10 seconds. Proposed retrieval approach was evaluated by 200 queries recorded from 5 male and 5 female speakers. In this work, we have asked each speaker to speak 20 speech documents from the speech database at random. The retrieval performance of the proposed method is shown in Table 1. From the results presented in Table 1, it is observed that the accuracy of retrieval is 88% for the male speaker queries and 3% for female speaker queries. The reason behind the queries being missed is that the speakers are different, and thus their utterances of the similar text may differ. These differences account for the differences in the sequences we are matching. Therefore, if the utterance differs at many places, the sequences get altered immensely resulting in query misses. The gender effect on the MFCC vectors, also plays a role in poor retrieval performance of the female speaker queries.

Table 1. Retrieval performance with longest common subsequence matching

Speaker Gender			
Male		Female	
Speaker Id	Queries matched	Speaker Id	Queries matched
1	18	6	0
2	20	7	0
3	15	8	2
4	20	9	0
5	15	10	1

The poor retrieval performance for the queries of female speakers may be due to the influence of gender characteristics. As the database contains only male speaker's speech utterances, therefore in case of female speakers queries, the indices generated by the queries is entirely different due to differences in shape and size of the vocal tract between the genders.

4 Summary and Conclusions

In this paper, a k-d tree based speech document indexing system has been proposed. For retrieving the desired speech document for a given query, the sequence of codebook indices, generated by the speech document and the query are compared using LCS approach. By computing the LCS scores between a query and all the speech documents, the retrieval system retrieves the desired document based on the highest LCS score. For evaluating the proposed retrieval approach, 3 hours of speech database recorded by a male speaker was used. The performance accuracy in the retrieval process is found to be better for the queries spoken by male speakers. In the case of female speakers, the performance is observed to be very poor.

In this work, the codebooks are generated from each 10 second speech document. The codebook captures the local characteristics of speech present in that 10 second segment. Therefore when we generate the indices from this codebook, the sequence of indices may be differ for different speakers even if the spoken message content is same. This problem may be addressed by building a single codebook from large amount of speech data instead of smaller codebooks for each 10 second segment. From the generalized codebook, if we derive the sequence of indices for the speech document and the query, the retrieval accuracy may be improved. It may also resolve the problem risen due to gender dependent query. Query gender dependency may also be resolved by adapting appropriate vocal tract length normalization(VTLN) feature transformation techniques in the codebook building procedure. Also, in the current experimental setup the queries given were similar to clips present in the speech database. In future, work can be done to perform retrieval based on queries having only few keywords and other connecting words.

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An Improved Filtered-x Least Mean Square Algorithm for Acoustic Noise Suppression

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Abstract. In the modern age scenario noise reduction is a major issue, as noise is responsible for creating disturbances in day-to-day communication. In order to cancel the noise present in the original signal numerous methods have been proposed over the period of time. To name a few of these methods we have noise barriers and noise absorbers. Noise can also be suppressed by continuous adaptation of the weights of the adaptive filter. The change of weight vector in adaptive filters is done with the help of various adaptive algorithms. Few of the basic noise reduction algorithms include Least Mean Square algorithm, Recursive Least Square algorithm etc. Further we work to modify these basic algorithms so as to obtain Normalized Least Mean Square algorithm, Fractional Least Mean Square algorithm, Differential Normalized Least Mean Square algorithm, Filtered-x Least Mean Square algorithm etc. In this paper we work to provide an improved approach for acoustic noise cancellation in Active Noise Control environment using Filtered-x LMS (FXLMS) algorithm. A detailed analysis of the algorithm has been carried out. Further the FXLMS algorithm has been also implemented for noise cancellation purpose and the results of the entire process are produced to make a comparison.

Keywords: adaptive filter, active noise control, Least Mean Square, Mean Square Error, FXLMS.

1 Introduction

Active noise control (ANC) is based on the principle of destructive superposition of acoustic waves [1, 2]. Using ANC concept in noise cancellation, a noise signal is generated which is correlated to the noise signal but opposite in phase. By adding both the original signal can be made noise free. The generation of the signal is controlled by an adaptive algorithm which adaptively changes the weight of the filter used. Active noise control is mainly classified into two categories i.e. “feed-forward ANC” and “feedback ANC”. In feedback ANC method a controller is used to modify the response of the system. But in feed-forward ANC method a controller is used to

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adaptively calculate the signal that cancels the noise. In this paper "feed-forward ANC" approach is implemented to cancel the noise with the help of FxLMS algorithm. This is because the amount of noise reduction achieved by feed-forward ANC system is more than that of feedback ANC system. A single channel feed-forward ANC system comprises of a reference sensor, a control system, a cancelling loudspeaker and an error sensor. The primary noise present is measured by the reference sensor and is cancelled out around the location of the error microphone by generating and combining an anti-phase cancelling noise that is correlated to the spectral content of the unwanted noise [3]. The reference sensor produces a reference signal that is "feed-forward" to the control system to generate "control signals" in order to drive the cancelling loudspeaker to generate the cancelling noise. The error microphone measures the residual noise after the unwanted noise and controls signal. It combines and sends an error signal back to the controller to adapt the control system in an attempt to further reduction of error. The control system adaptively modifies the control signal to minimize the residual error. The most famous adaptation algorithm for ANC systems is the FXLMS algorithm [4, 5] as mentioned earlier, which is a modified and improved version of the LMS algorithm [6-10].

Although FXLMS algorithm is widely used due to its stability but it has slower convergence. Various techniques have been proposed to improve the convergence of FXLMS algorithm with some parameter trade-offs. Other versions of the FXLMS include Filtered-x Normalized LMS (FXNLMS) [11], Leaky FXLMS [12], Modified FXLMS (MFXLMS) [13-15] etc. However, the common problem with all of these algorithms is the slow convergence rate, especially when there is large number of weights [16]. To overcome this problem, more complex algorithms such as Filtered-x Recursive Least Square (FXRLS) [17] can be used. These algorithms have faster convergence rate compared to the FXLMS; however they involve matrix computations and their real-time realizations might not be cost effective.

2 Problem Formulation

Acoustic noise problems are not only based on high frequency noise but many are also dominated by low frequency noise. Various passive noise control techniques such as noise barriers and absorbers do not work efficiently in low frequency environments. ANC works very efficiently in case of low frequency noise & it is also cost effective than bulky, heavy barriers and absorbers.

The basic LMS algorithm fails to perform well in the ANC framework. This is due to the assumption made that the output of the filter is the signal perceived at the error microphone, which is not the case in practice. The presence of the A/D, D/A converters, actuators and anti aliasing filter in the path from the output of the filter to the signal received at the error microphone cause significant change in the output signal. This demands the need to incorporate the effects of this secondary path function in the algorithm. But the convergence of the LMS algorithm depends on the phase response of the secondary path, exhibiting ever-increasing oscillatory behavior as the phase increases and finally going unstable at 90° [11]. The solution to this problem was either to employ an inverse filter in the cancellation path or to introduce a filter in the reference path, which is ideally equal to the secondary path impulse response. The former technique is referred to as the “filtered-error” approach, while the later is now known as the “filtered-reference” method, more popularly known as the FXLMS algorithm. The FXLMS solution is by far the most widely used due to its stable as well as predictable operation [3-5].

3 Simulation Setup

1) Feed-forward ANC system:

The basic idea of feed-forward ANC is to generate a signal (secondary noise), that is equal to a disturbance signal (primary noise) in amplitude and frequency, but has opposite phase. Combination of these signals results in cancellation of the primary (unwanted) noise. This ANC technique is well-known for its use in cancelling unwanted sound as shown in [2].

2) ANC system description using adaptive filter:

In this paper instead of the adaptive algorithm block an improved FXLMS algorithm approach is employed to suppress noise. The most popular feed-forward control algorithm for acoustic noise cancellation is FXLMS algorithm [7] which is the main area of focus in this paper. A control signal is created by the FXLMS algorithm by filtering the reference signal $x(n)$ with an adaptive control filter. The control filter is updated via a gradient descent search process until an ideal filter that minimizes the residual noise found. This is because the existence of a filter in the auxiliary and the error- path is shown which generally degrade the performance of the LMS algorithm. Thus, the convergence rate is lowered, the residual power is increased and the algorithm can even become unstable. In order to stabilize LMS algorithm, the reference signal $x(n)$ is filtered by an estimate of the secondary path transfer function $S(n)$ which is the propagation path from the controller to the error sensor giving the filtered-x signal. Hence the algorithm is known as FXLMS algorithm.

The noise measured at the reference sensor propagates through the primary path represented by $P(n)$ and arrives at the error sensor or receiver as the signal, $d(n)$. This is the unwanted noise to be cancelled which is sometimes referred to as the “desired” signal, meaning the signal that the controller is trying to duplicate with opposite phase. The desired signal will be correlated with the noise characterized by the reference. The LMS algorithm then generates control signal at the cancelling loudspeaker by filtering the reference signal $x(n)$ with an adaptive FIR control filter, $W(n)$. The control signal, $y(n)$, is the convolution of $x(n)$ with $W(n)$.The control signal is filtered by the secondary path transfer function, $S(n)$, and arrives at the error sensor as the output signal, $y'(n)$.The output signal combines with the unwanted noise to give the residual error signal, e(n), measured by the error sensor. An adaptive process searches for the optimal coefficients for the control filter which minimizes the error. This optimal filter is designated W_{opt} [7-10].

Step:1

For ANC system containing a Secondary Path transfer function $S(n)$ the residual error can be expressed as:

$$e(n) = d(n) - y'(n) \tag{1}$$

where, $y'(n)$ is the output of the secondary path $S(n)$.

Step:2

If $S(n)$ be an IIR filter with denominator coefficients $[a_0 ......a_n]$ and numerator coefficient $[b_0 ....b_{M-1}]$, then the filter output $y'(n)$ can be written as the sum of the filter input $y(n)$ and the past filter output:

$$y'(n) = \sum_{i=1}^{N} a_i y'(n-i) + \sum_{j=0}^{M-1} b_j y(n-j) \tag{2}$$

Step:3

Hence the gradient estimate becomes:

$$\nabla \hat{\xi}(n) = -2x'(n)e(n), \tag{3}$$

where,
$$x'(n) = \sum_{i=1}^{N} a_i x'(n-i) + \sum_{j=0}^{M-1} b_j x(n-j) \tag{4}$$

In practical applications, $S(n)$ is not exactly known, therefore the parameters a_i and b_j are the parameters of the Secondary Path Estimate $\hat{S}(n)$.

Step:4

The weight update equation of the FXLMS algorithm is:

$$w(n+1) = w(n) + \mu x'(n)e(n) \tag{5}$$

Equation (5) is the filter weight update equation of the FXLMS algorithm. As it can be seen that the equation is identical to the LMS algorithm but here instead of using x(n) i.e. the reference signal, $x'(n)$ is used which is the filtered output of the original signal called as “filtered-x signal” or “filtered reference signal”.

The FXLMS algorithm is very tolerant to modelling errors in the secondary path estimate. The algorithm will converge when the phase error between $S(n)$ and $H(n)$ is smaller than +/- 90 degrees. Computer simulations show that phase errors less than 45º do not significantly affect performance of the algorithm [8]. The gain applied to the reference signal by filtering it with $S(n)$ does not affect the stability of the algorithm and is usually compensated for by modifying the convergence parameter, μ. Convergence will be slowed down though, when the phase error increases. $H(n)$ is estimated through a process called system identification. Band-limited white noise is played through the control speaker(s) and the output is measured at the error sensor.

The measured impulse response is obtained as a FIR filter $S(n)$ in the time domain. The coefficients of $S(n)$ are stored and used to pre-filter the reference signal and give the input signal to the LMS update.

The performance of the FXLMS adaptation process is dependent on a number of factors. Those factors include the characteristics of the physical plant to be controlled, the secondary path impulse response and the acoustic noise band-width. Hence the FXLMS will not function properly if the secondary path has a long impulse response and/or the acoustic noise has a wide band-width. Among the design parameters, steady state performance increases, increasing the filter length but convergence of FXLMS algorithm is degraded by this. So the filter length should be chosen carefully. After the filter length is set, the maximum achievable performance is limited by a scalar parameter called the adaptation step-size. The speed of convergence will generally be higher when choosing a higher sample frequency and higher value of μ. [14-16]

It is advantageous to choose a large value of μ because the convergence speed will increase but too large a value of μ will cause instability. It is experimentally determined that that the maximum value of the step size that can be used in the FXLMS algorithm is approximately:

$$\mu_{\max} = \frac{1}{p_{x'}(L+\Delta)} \tag{6}$$

where $p_{x'} = E[x'^2(n)]$ is the mean-square value or power of the filtered reference signal $x'(n)$, L is the number of weights and Δ is the number of samples corresponding to the overall delay in the Secondary Path.

After convergence, the filter weights $W(n)$ vary randomly around the optimal solution W_{opt}. This is caused by broadband disturbances, like measurement noise and impulse noise on the error signal. These disturbances cause a change of the estimated gradient $\nabla\hat{\xi}(n)$, because it is based only on the instantaneous error. This results in an average increase of the MSE, that is called the excess MSE, defined as, [9]

$$\xi_{excess} = E[\hat{\xi}(n)] - \xi_{\min} \tag{7}$$

This excess MSE is directly proportional to step size. It can be concluded that there is a design trade-off between the convergence performance and the steady-state performance. A larger value of μ gives faster convergence but gives bigger excess MSE and vice-versa. Another factor that influences the excess MSE is the number of weights.

4 Simulation and Results

MATLAB platform is chosen for simulation purpose. The room impulse response is measured for an enclosure of dimension 12×12×8 ft^3 using an ordinary loudspeaker and an uni-dynamic microphone kept at a distance of 1 ft which has been sampled at 8 KHZ. The channel response is obtained by applying a stationary Gaussian stochastic signal with zero mean and unit variance as input on the measured impulse response. Fig. 1 shows the MATLAB simulation of noise cancellation.

Fig. 1 (a) is the original noise, (b) is the noise observed at the headset. Fig. 1(c) is the inverse noise generated by an adaptive algorithm using the DSK, and Fig. 1(d) is the error signal between the noise observed at the headset and the inverse noise generated by the DSK. Fig. 1(d) shows that the error signal is initially very high, but as the algorithm converges, this error tends to zero thereby effectively cancelling any noise generated by the noise source.

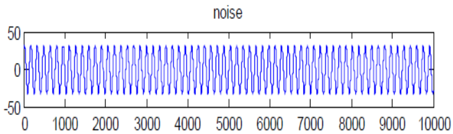

Fig. 1(a). Original noise

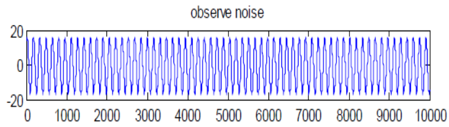

Fig. 1(b). Observed noise

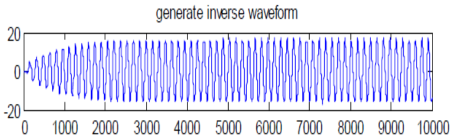

Fig. 1(c). Inverse noise generated by adaptive algorithm

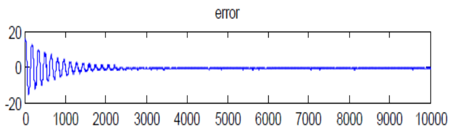

Fig. 1(d). Error signal

The primary and secondary path impulse response with respect to time is presented in Fig. 2 and Fig. 3 respectively. The first task in active noise control is to estimate the impulse response of the secondary propagation path. This is usually performed prior to noise control using a random signal played through the output loudspeaker while the unwanted noise is not present. Fig.4 shows the true estimation of secondary path impulse response with the variation in coefficient value for the true, estimated and error signal with respect to time. The performance of FXLMS algorithm for ANC can be judged from the discussed results pertaining to an adaptive framework.

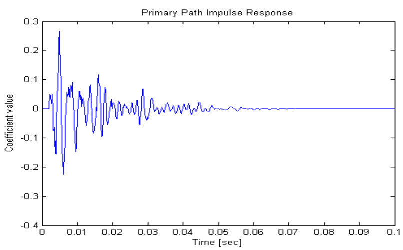

Fig. 2. Primary path impulse response

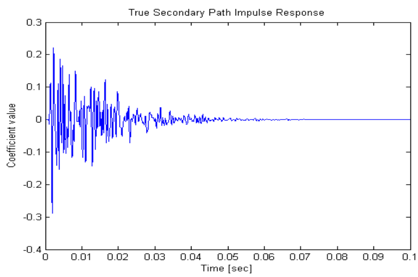

Fig. 3. True secondary path impulse response

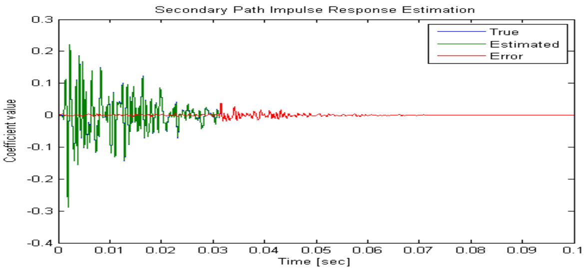

Fig. 4. True estimation of Secondary path impulse response

5 Conclusion

FXLMS Algorithm is widely used in acoustic noise cancellation environment due to its simple real time implementation & low computational complexity. Although the algorithm has slow convergence but various modifications in the existing circuit can be done to improve the convergence. FXLMS algorithm has greater stability than other algorithms used in case of acoustic noise cancellation as shown in the paper. There is a wide range of modification scopes available in case of FXLMS algorithm which can improve the convergence. FXLMS algorithm can also be used in very high noise environment.

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A Unique Low Complexity Parameter Independent Adaptive Design for Echo Reduction

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Abstract. Acoustic echo is one of the most important issues in full duplex communication. The original speech signal is distorted due to echo. For this adaptive filtering is used for echo suppression. In this paper our objective is to cancel out the acoustic echo in a sparse transmission channel. For this purpose many algorithms have been developed over the period of time, such as Least Mean Square (LMS), Normalized LMS (NLMS), Proportionate NLMS (PNLMS) and Improved PNLMS (IPNLMS) algorithm. Of all these algorithms we carry out a comparative analysis based on various performance parameters such as Echo Return Loss Enhancement, Mean Square Error and Normalized Projection Misalignment and find that for the sparse transmission channel all these algorithm are inefficient. Hence we propose a new algorithm modified - μ - PNLMS, which has the fastest steady state convergence and is the most stable among all the existing algorithms, this we show based on the simulation results obtained.

Keywords: Acoustic Echo, Adaptive Filter, Echo Return Loss Enhancement, LMS, Mean Square Error, Sparse Transmission Channel.

1 Introduction

Echo is a delayed and distorted version of the original signal. Acoustic echo is mainly present in mobile phones, Hands free phones, Teleconference or Hearing aid systems which is caused due to the coupling of microphone & loudspeaker. Echo largely depends on two parameters: amplitude & time delay of reflected waves. Usually we consider echoes with appreciable amplitude & larger delays of above 1 ms, but in certain cases if the generated echo is above 20 ms then it becomes a major issue and needs to be cancelled. Thus, developers are using the concepts of Digital Signal Processing for echo cancellation to stop the undesired feedback and allow successful full duplex communication. [1]

To achieve echo free systems numerous methods have been proposed like echo absorbers, echo barriers, echo cancellers to name a few. But considering the

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advancement of signal processing echo cancellation can be best done by the help of adaptive filtering. Adaptive filters are widely used due to its stability and wide scope for improvements. Adaptive filters can also be applied to low frequency noise. Echo can be suppressed in the most effective manner by continuous adaptation of the weights of the adaptive filter till the echo is completely cancelled out. System identification is generally used to generate a replica of the echo that is subtracted from the received signal. The echo canceller should have a fast convergence speed so that it can identify and track rapidly the changes in the unknown echo path. The convergence rate depends on the adaptive algorithm as well as the structure of adaptive filter used in AEC. In AEC, a signal is generated which is correlated to the echo signal but opposite in phase. By adding both the signals that is the signal corrupted by noise and the generated signal which is correlated and opposite phase to the actual echo signal, original signal can be made echo free. The generation of the signal is controlled by an adaptive algorithm which adaptively changes the weight of the filter used. AEC is classified into two categories i.e. “feed-forward AEC” and “feedback AEC”. In feedback AEC method we use a controller to modify the response of the system. The controller may be like an addition of artificial damping. But in feed-forward AEC method a controller is used to adaptively calculate the signal that cancels the noise. In this paper “feed-forward AEC” approach is implemented to cancel the echo. This is because the amount of echo reduction achieved by feed-forward AEC system is more than that of feedback AEC system [2].

Further the nature of the transmission channel in AEC being sparse i.e. only few weight coefficients are active and all others are zero or tending to zero. The basic fundamental algorithms like LMS and NLMS suffer from slow convergence speed in these sparse channels. Hence a new modified algorithm was developed by Duttweiler named Proportionate NLMS for the sparse transmission channel systems [3]. The concept behind this is to assign each coefficient a step size proportionate to its estimated magnitude and to update each coefficient of the adaptive filter independently. But the main issue with the algorithm is that the convergence speed is reduced excessively after the initial fast period. A new kind of adaptive filtering process μ PNLMS was proposed to encounter the aforesaid problem. Here, the logarithm of the magnitude is used as the step gain of each coefficient instead of magnitude only. So this algorithm can consistently converge over a long period of time.

In this paper, we propose an algorithm to improve the performance of the MPNLMS algorithm to a greater extent in the sparse channel. The proposed algorithm adaptively detects the channel’s sparseness and changes the step size parameter to improve the ERLE, Mean Square Error (MSE) and Normalized Projection Misalignment (NPM).

2 Existing Algorithms for AEC

A. LMS & NLMS:

It is one of the most widely used algorithms which has a weak convergence but is easy to use and is stable. It has two inputs one of which is the reference noise that is related with the noise that exits in the distorted input signal. The weight update equation for the LMS algorithm is given by:

$$\hat{h}(n+1) = \hat{h}(n) + 2x(n+1)e(\mathrm{n}+1) \tag{1}$$

In case of LMS algorithm if the step size is too small then the adaptive filter will take too much time to converge, and if it is too large the adaptive filter becomes unstable and its output diverges .So it fails to perform well in echo cancellation. The recursive formula for Normalized Least mean Square (NLMS) algorithm is

$$\hat{h}(n+1) = \hat{h}(n) + 2\mu \frac{x(n+1)e(\mathrm{n}+1)}{\| x(n+1) \|_2^2 + \delta_{NLMS}} \tag{2}$$

Here δ_{NLMS} is the variance of the input signal $x(n)$ which prevents division by zero during initialization stage when $x(n) = 0$ .Further to maintain stability the step size should be in the range $0 < \mu < 2\frac{E\{| \mathrm{x(n+1)} |^2\}D(n+1)\}}{E\{| e(n+1) |^2\}}$.

Here $E\{| x(n) |^2\}$ is the power of input signal, $E\{| e(n) |^2\}$ is the power of error signal and $D(n)$ is the mean square deviation . The NLMS algorithm though being efficient does not take into consideration sparse impulse response caused to bulk delays in the path and hence needs to adapt a relatively long filter. Also unavoidable noise adaptation occurs at the inactive region of the filter. To avoid this we need to use sparse algorithms, where adaptive step size are calculated from the last estimate of the filter coefficients in such a way that the step size is proportional to step size of filter coefficients. So active coefficients converge faster than non-active ones and overall convergence time gets reduced. [4]

B. PNLMS

In order to track the sparseness measure faster PNLMS algorithm was developed from NLMS equation. Here the filter coefficient update equation is different from the NLMS in having a step size update matrix Q, with rest of the terms remaining same and is given below as:

$$\hat{h}(n+1) = \hat{h}(n) + \mu \frac{Q(n)x(n+1)e(\mathrm{n}+1)}{\| x(n+1) \|_2^2 + \delta_{PNLMS}} \tag{3}$$

Here, $\delta_{PNLMS} = \delta_{NLMS} / L$, and the diagonal matrix Q (n) is given by,

$$Q(n) = diag\{q_0(n), q_1(n)............q_{l-1}(n)\}$$

Here $q_l(n)$ is the control matrix and is given by ,

$$q_l(n) = \frac{k_l(n)}{\frac{1}{L}\sum_{i=0}^{L-1} k_i(n)} \tag{4}$$

Also $k_l(n) = \max\{\rho \times \max\{\gamma, |\hat{h}_0(n)|, \ldots. |\hat{h}_{l-1}(n)|\}, |\hat{h}_l(n)|\}$

Here ρ and λ have values 5/L and 0.01 respectively. ρ prevents coefficients from stalling when they are smaller than the largest coefficient and also prevents $\hat{h}_l(n)$ from stalling during the initialization stage. [5]

C. IPNLMS:

It is an improvement over the PNLMS algorithm and employs a combination of proportionate (PNLMS) and non-proportionate (NLMS) updating technique, with the relative significance of each controlled by a factor α . Thus we have value of $k_l(n)$ as

$$k_l(n) = \frac{1-\alpha}{2L} + (1+\alpha)\frac{|h_l(n)|}{2\,\|h(n)\|_1 + \varepsilon} \tag{5}$$

here ε is a small positive constant .Also results so that good choice for α are 0.-0.5,-0.75. The regularization parameter should be taken such so that same steady state misalignment is achieved compared to that of NLMS using same step size. [6] We have

$$\delta_{IPNLMS} = \frac{1-\alpha}{2L}\delta_{NLMS} \tag{6}$$

D. MPNLMS:

This algorithm is an efficient one for a sparse transmission channel and has a steady convergence over a period of time. Unlike the previously discussed proportionate algorithms which have a faster convergence during the initial period but slows down over a period of time. In this algorithm we calculate the step size proportionate to the logarithmic magnitude of the filter coefficients. [7]

3 Proposed Algorithm

Among all the algorithms discussed above for a sparse channel, which is our transmission channel of interest, the μ-PNLMS algorithm has the fastest convergence. The existing classical NLMS algorithm's filter weight coefficients converge slowly in such a channel. Hence PNLMS and IPNLMS algorithms were designed specifically for echo cancellation in sparse transmission channels, but after initial fast convergence of filter weight vectors, these algorithms too fail.[6]-[7] So we propose μ -law PNLMS algorithm for a sparse channel. Here instead of using filter weight magnitudes directly, its logarithm is used as step gain of each coefficient. Hence μ -PNLMS algorithm can converge to a steady state effectively for a sparse channel. This algorithm calculates the optimal proportionate weight size in order to achieve fastest convergence during the whole adaptation process until the adaptive filter reaches its steady state.

Implementation:

Step 1: The weight update equation for the proposed algorithm is given as:

$$\hat{\mathrm{h}}(n+1) = \hat{h}(n) + \mu \frac{Q(n)x(n+1)e(\mathrm{n}+1)}{\| x(n+1) \|_2^2 + \delta_{MPNLMS}} \tag{7}$$

where;

$$\delta_{MPNLMS} = \delta_{NLMS} \big/ L \tag{8}$$

Step 2: The control matrix $q_l(n)$ which is the matrix containing the diagonal elements of the $Q(n)$ is given as,

$$q_l(n) = \frac{k_l(n)}{\frac{1}{L} \sum_{i=0}^{L-1} k_i(n)} \tag{9}$$

Step 3: Finally the value of $k_l(n)$, which is the main differentiating factor in case of the proposed algorithm is given as:

$$\mathrm{k}_l(\mathrm{n}) = \max\{\rho \times \max\{\gamma, \mathrm{F}(|\hat{\mathrm{h}}_0(\mathrm{n})|) \ldots\ldots\ldots\ldots \mathrm{F}(|\hat{\mathrm{h}}_{l-1}(\mathrm{n})|)\}, F(|\hat{\mathrm{h}}_l(n)|)\} \tag{10}$$

Here,

$$F(|\hat{\mathrm{h}}_l(n)|) = \frac{\ln(1+\mu |\hat{h}_l(n)|)}{\ln(1+\mu)}, \tag{11}$$

$|\hat{\mathrm{h}}_L(n)| \leq 1$ and $\mu = 1/\varepsilon$. Constant 1 is taken inside the algorithm to avoid infinity value when the value of $|\hat{\mathrm{h}}_l(n)|$=0 initially. The denominator $\ln(1+\mu)$ normalizes $F(|\hat{\mathrm{h}}_L(n)|)$ in the range [0, 1].The value of ε should be chosen based on the noise level and usually it is taken as 0.001.

4 Results and Discussion

MATLAB platform is chosen for simulation purpose. The room impulse response is measured for an enclosure of dimension 12×12×8 ft^3 using an ordinary loudspeaker and an uni-dynamic microphone kept at a distance of 1 ft. which has been sampled at 8 KHZ. The channel response is obtained by applying a stationary Gaussian stochastic signal with zero mean and unit variance as input on the measured impulse response.

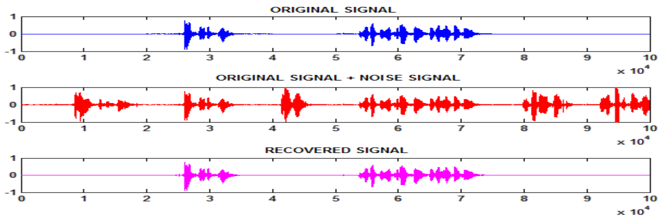

Fig. 1. AEC using proposed Algorithm

Fig. 1 shows the MATLAB simulation of acoustic echo cancellation using the proposed algorithm. Fig.1 has three separate graphs where the first is the original noise present in the system ,the second one is the graph of original signal along with the noise signal and the third graph is the original signal recovered using the proposed algorithm.

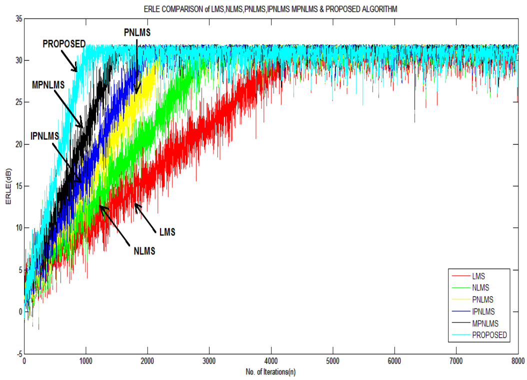

Fig. 2. ERLE Comparison of existing and proposed algorithms

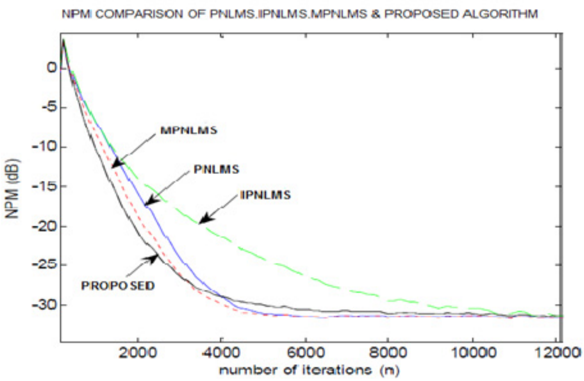

Fig. 3. NPM comparison of existing and proposed algorithms

In Fig. 2 we show the ERLE comparison of PNLMS, IPNLMS, $\mu-$PNLMS and the proposed algorithm, the result clearly shows that the ERLE for the proposed algorithm is maximum. Further in Fig. 3 we show the comparative analysis of NPM of PNLMS, IPNLMS, $\mu-$PNLMS and the proposed algorithm which clearly indicates that has the least value for our proposed algorithm.

The analysis is carried out by taking a signal $x(n)$ as an input to the various adaptive algorithms and the desired signal is taken as $d(n)$ .The error signal thus generated is minimized continuously in an adaptive manner by setting the step size to an optimum value. Our aim is to obtain the quickest steady state convergence for minimizing the error or the acoustic echo, which is obtained using our proposed algorithm. This can be shown through the comparison of ERLE and NPM for all the algorithms including our proposed algorithm. And based on our simulation results we obtain that our proposed algorithm has the maximum ERLE and the least NPM value among all the algorithms such as PNLMS, $\mu-$PNLMS and IPNLMS.

5 Conclusion

In this paper we do a detailed study of the existing algorithms for acoustic echo cancellation and find out that only proportionate algorithms are capable of acoustic echo cancellation in sparse channel. But among the existing proportionate algorithms PNLMS, IPNLMS though have initial fast convergence they fail to adapt as time progresses [7]. And only $\mu-$PNLMS algorithm has a good steady state convergence. Now to further improve the performance of $\mu-$PNLMS algorithm we propose our own algorithm which we have shown to have the most efficient steady state convergence for transmission channels having sparse impulse response. This we ascertain based on our simulation results, where we take into consideration various performance measurement parameters like ERLE and NPM.We have obtained that our algorithm gives the maximum ERLE amongst all the existing algorithm and also the least NPM value. So we can safely conclude that our proposed algorithm is the most efficient one for acoustic echo cancellation in a sparse medium.

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On the Dissimilarity of Orthogonal Least Squares and Orthogonal Matching Pursuit Compressive Sensing Reconstruction

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Abstract. Compressive sensing is a recent technique in the field of signal processing that aims to recover signals or images from half samples that were used by Shannon Nyquist theorem of reconstruction. For recovery using compressed sensing, two well known greedy algorithms are used- Orthogonal matching pursuit and orthogonal least squares. Generally these two algorithms are taken as same by the researchers which is not true. There is a remarkable difference between the two algorithms that is pointed out in this paper with the simulation results. The previous article clarifying the difference between these two algorithms are emphasized on theoretical difference and does not show any reconstruction simulation difference with these two algorithms and reason to preference over basis pursuit method . The key aim of this paper is to remove the confusion between the two algorithms on the basis of theory and reconstruction time taken with the output PSNR.

Keywords: Compressive sensing, Reconstruction, Orthogonal least squares, orthogonal matching pursuit.

1 Introduction

Compressed sensing is an innovative theory in the field of signal processing that aims to reconstruct signals and images from what was previously treated as incomplete information. It uses relatively few measurements than those were needed in the Shannon Nyquist theory of signal reconstruction. This theory comes from the fact that most of the signal information is carried by only few of coefficients and all other are get wasted while reconstructing that signal [1]. Then it gives a way to collect only those components in the first stage that adds up in signal recovery. The practical need of this study comes with the shortage of storage space for increasing data transferred from here to there.

Compressed sensing has been used in many fields like medical imaging, Radar, Astronomy, speech processing where the task is to reconstruct a signal. For example, in medical imaging CT (computerized Tomography), by exposing x-rays one can generate image of inside of human body. For the complete scanning process, patient is

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exposed to radiations for a large span of time, which are harmful for him. By using compressive sensing, only the desired samples are to be taken, so scanning time reduces to a great extent by decreasing the number of samples to be taken. The mechanism of reconstruction using sparse matrix is shown in Fig. 1.

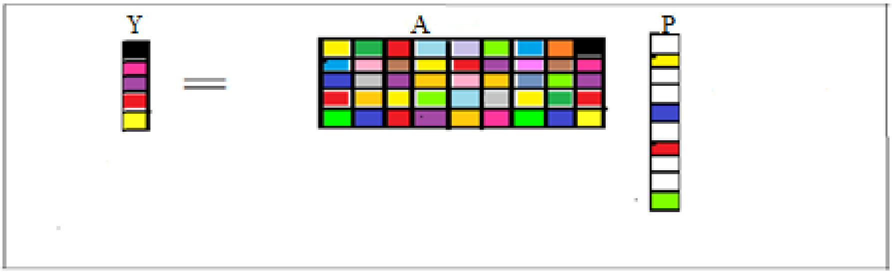

Fig. 1. Compressed sensing framework

Where Y is the reconstructed signal and A' is the random measurement matrix. Gaussian and Bernoulli matrices are mostly used as random measurement matrices. For Gaussian matrices the elements are chosen randomly as independent and identically distributed. These elements can have the variance as from [3]

$$\text{Variance}=1/K$$

For the Bernoulli matrices [3] with equal probability each element takes value of $1/\sqrt{K}$ or $+1/\sqrt{K}$

For reconstruction using compressed sensing two type of algorithm are used basis pursuit and greedy algorithms. Basis pursuit algorithms are quite simpler to implement as compared to greedy pursuit. The greedy algorithms generally used are orthogonal matching pursuit and orthogonal least squares give faster recovery. Generally these two algorithms are taken as same but there is certain difference in them [8]. For the greedy algorithms, the projection on selected signal elements is orthogonal. OLS selects the entity that minimizes the residual norm after signal's projection onto the selected entities [4]. It has been proved by Thomas Blumensath and Mike E. Davies in [4]. This particular entry is the one which best approximates the current residual. This marks the difference of OLS from OMP. Generally OLS is little bit more complex than OMP, but due to the same output results given by two algorithms, both are taken as same by the researchers. There had been previous work on clarification between two algorithms, but most of it is based on theoretical concepts. In this paper the confusion on the similarity part of both algorithms is removed by showing the simulation results of both the algorithms for same results. The reconstruction time taken by both is also considered.

2 Orthogonal Matching Pursuit

Tropp and Gilbert had given an idea for orthogonal matching pursuit algorithm for reconstruction with less number of measurements [5-6]. It has been proved in the literature by Huang and Rebollo that reconstruction time can be reduced to a great extent by using this particular algorithm [13], [15]. Suppose that the column vector of A are normalized such that

$$\| A_i \|_2=1, \text{ for } i=1,2,\ldots k$$

A(x) be a subset of A for x C {1,2,..,k}. To start the algorithm, signal support is needed to be calculate from pseudo inverse A` of the measurement matrices A, as

$$P= (A)`Y$$

Where A' is the complex conjugate of measurement matrices A and we know that

$$A`= (A^*A)^{-1}A^*$$

During the implementation a matching operation is performed between the matrix A entries and the calculated residuals of P [2, 14]. At the end of all iterations, the complete signal is generated. The implemented algorithm includes following steps

1. Initialize the residual of Y as $s_0 = y$
2. Initialize the set of entries that are to be selected as A(c)= null
3. Start an iteration counter. Let i=1
4. Generate an estimate of given signal per iteration.
5. Solve the maximization problem

   $$\max| A_j , s_{i-1} |$$

   In which A_j is any variable.
6. To A(c), the set of selected variables, add A_j , and update c after every result.
7. It is to be noted that the algorithm does not minimize the residual error after its orthogonal projection to the values.
8. Update result after the projection. The entry selected have a minimum error as

   $$r^n=S- S^n$$
9. One coordinate for signal support for P is calculated at the end after computing the residual.
10. Set i=i+1, to end the iterations of algorithm.

3 Orthogonal Least Squares

On the contrary to matching pursuit algorithm, there is another method in the literature based on least squares [7], [9]. In OLS, after the projection into the orthogonal subspace, OLS selects the element with smallest angle [4]. This element best approximates the current residual. For the least squares method, a vector is needed to be calculated of few non-zero elements such that the squared error is small [4]. That's why the name least squares is there. The vector calculated must be with dimensions

$$P \in D_K \text{ and}$$

$$A \in D^{Np * Ny}$$

An approximation to the signal P is calculated at the end of an iteration and result is updated after every sequence. The complete procedure goes same for least squares algorithm [12], [14]. Initially a counter is started and a residual is assumed and residual is updated after every projection result .This algorithm selects the entry having a minimum error from the sub matrix [4]. Just after the orthogonal projection step, the algorithm minimizes the residual error. The approximation error is given by

$$e^n = P - P^n$$

After the projection onto the signal entries, calculate the maximization problem as

$$j_{max} = \|A - (A^*_i A_i)^{-1} A\|_2$$

Solving A_i^{-1} is an inverse problem here. The pseudo inverse A_i^{-1} of the random measurement matrices is taken from

$$P_n = A_i^{-1} A$$

Thus the signal is reconstructed from the inverse problem solution [10].

4 Simulation Results and Analysis

The focus of this paper is to highlight difference between the two mentioned greedy algorithms. An estimate for matrix A is calculated and its columns are used to calculate the inner products required to select elements from signal. When the number of elements to be selected is quite smaller than the number of column vectors of matrix A; OLS is complex because all elements need to be orthogonalized [4].

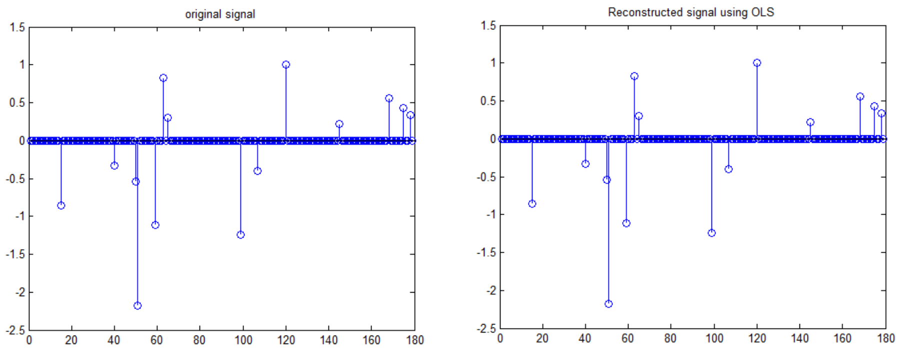

Fig. 2. (a) Original randomly generated signal (b) original signal reconstructed using Orthogonal Least Squares

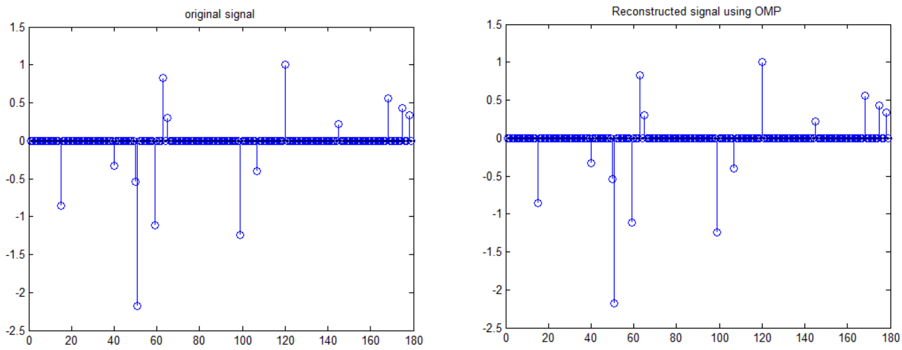

Fig. 3. (a) Original randomly generated signal (b) original signal reconstructed using Orthogonal Matching Pursuit

It has been proved previously that the greedy algorithms are faster than the basis pursuit compressive sensing reconstruction. This is shown in Fig.2(a),(b) and Fig.3(a),(b) A comparison of elapsed time for reconstruction and for PSNR for the output signal is shown in Table 1. A comparison of both the algorithms is done with Justin Romberg's Basis pursuit's algorithm [11].

Table 1. Comparison of elapsed time and PSNR for both the algorithms

Algorithm	Elapsed Time(s)	PSNR(db)
OLS	0.037765	83.5091
OMP	0.052453	83.5217
BP	0.731953	81.7943

In Table 1, the reconstruction time is given in seconds and is calculated from the beginning of the generation of sparse matrix up to the generation of output signal. A slight difference in PSNR is observed for the same signal recovery by using the two algorithms, which marks the difference between the two algorithms, i.e. proves that both are not same. The reconstruction results are obtained by implementing the greedy algorithms in a multi stage manner, with less number of dimensions. The PSNR obtained is higher than the L-norms or the basis pursuit method of compressive sensing reconstruction. It is clear from the table that greedy algorithms are faster than the basis pursuit algorithm.

5 Conclusions

The results from this paper demonstrate that both OLS and OMP algorithms gives same recovery results but there is a significant difference between the two in terms of