IMAGE & SIGNAL PROCESSING

A Dynamic MooM Dataset Processing Under TelMED Protocol Design for QoS Improvisation of Telemedicine Environment

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Abstract

Telemedicine research improves the connectivity of remote patients and doctors. Researchers are focused on data optimization and processing over a predefined channel of communication under a depictive low QoS. In this paper a consolidated representation of telemedicine infrastructure of modern topological arrangement is represented and validated. The infrastructure is aided with Multiple Objective Optimized Medical dataset (MooM) processing and a channel optimizing TelMED protocol designed exclusively for remote medicine dataset transmission and processing. The proposed infrastructure provides an application oriented approach towards Electronics health records (EHR) creation and updating over edge computation. The focus of this article is to achieve higher order of Quality of Service (QoS) and Quality of Data (QoD) compared to typical communication channels algorithms for processing of medical data sample. Typically the proposed technique results are achieved to discuss in MooM dataset processing and TelMED channel optimization sessions and a resulting improvement is discussed with a comparison of each MooM dataset in reverse processing towards server end of diagnosis and a consolidated QoS is retrieved for proposed infrastructure.

Introduction

Generally, Medical data processing is performed over a stand-alone system or in a static infrastructure such as diagnosis centers, hospitals and care-centers. With Information and Communication Technology's (ICT) modernization in medical diagnosis, Teleconsultation and Telecommunication is supported. Various developed nations have inculcated tele-medicine as a routine of healthcare monitoring and communication. Typically, telemedicine is defined as a connectivity bridge over ICT to connect remote patients with doctors [1]. Demonstrates a detailed study of ICT's role in building tele-medicine for developing countries like India, Bangladesh and Pakistan. A detailed insight is provided towards challenges

and barriers for telemedicine in developing countries and one such is Quality of Service (QoS) and Quality of Data (QoD) for diagnosis.

Telemedicine is expanding, with added artificial intelligence and machine learning terminologies for detection and diagnosis, the accuracy rate is improved and enhanced. Researchers are focused on various techniques towards detection and prediction of medical disabilities in data-samples. According to a study, the convertible rate of medical data processing techniques and algorithms is 42.3% and major lack is due to the environmental setup in ideal or close to idea processing under 0% dynamic challenges such as data losses, blind-third party algorithms, connectivity, Signal to Noise Ratio (SNR) or PSNR, accuracy rate and many. Thus research challenges are open in managing data ratio under channel for processing and binding the proposed or current processing technique in ideal environment to achieve a higher order of accuracy rate in diagnosis.

In the proposed technique, an initiative is taken to bridge the research gap between data-samples collection, transmission on channel and processing in idea environment. The technique is novel in its kind as it incorporates multi-objective data-types such as images, signals and text records.

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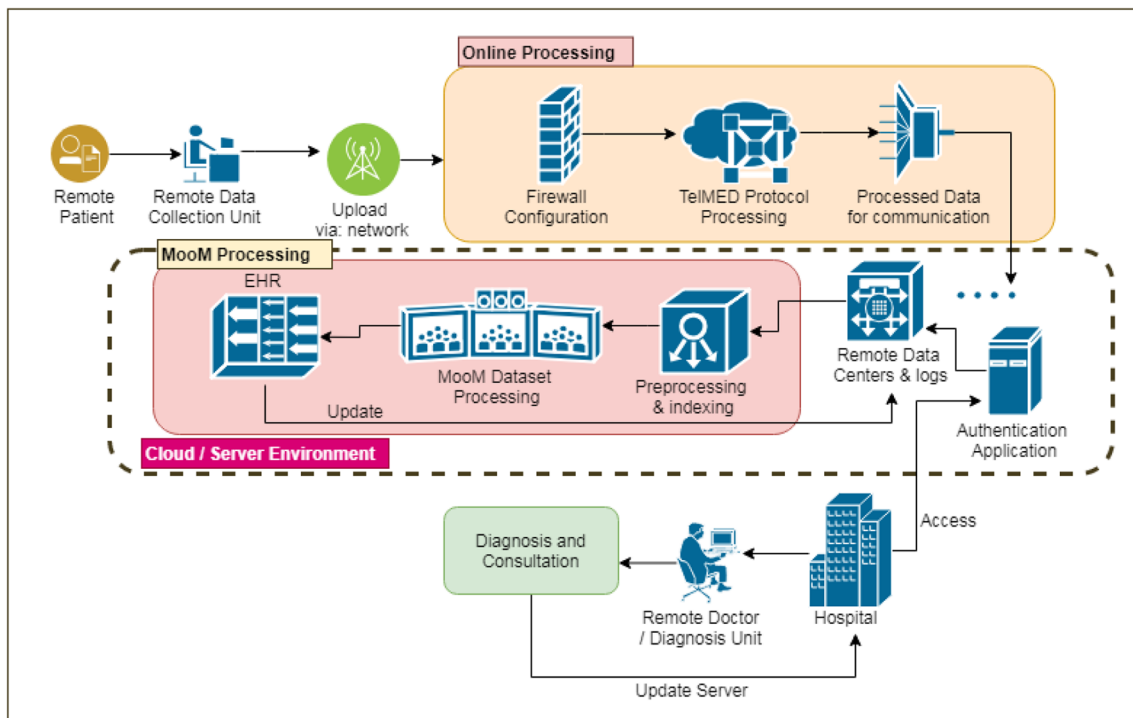   Crescent Institute of Science and Technology, Chennai, India

Fig. 1 Block diagram of proposed system architecture

The medical data samples are termed as Multi-Objective Optimized Medical (MooM) data, typically covering medical images, signals and text data. The technique is also processed on a defined protocol of communication, designed to perform medial data transmission over low line communication channels, known as TelMED (Telemedicine protocol). Thus, from the proposed methodology, a defined and optimized datasets are processed and diagnosed using standard third party medical processing techniques discussed in session of methodology.

Literature reviews

Medical data processing research has challenges unseen towards physical cases and scenarios of evaluation. In [2] a detailed survey of 248 research papers over various search engines and repositories is conducted for QoS and Quality of Experience (QoE), the authors provide a statistical information on relevance of telemedicine data processing over defined interest goals [3, 4] provides a defined infrastructure for designing telemedicine services over a WiMax and Open channel. Systematic software components required for implementation of telemedicine is studied by [4] and an economical software and IoT based device implementation for data collection over remote patients is discussed by [5]. Challenges and barriers for data processing under telemedicine is studied and reported across 30 research papers by [6] with results demonstrating 11% occurrence of challenges is due to technical or engineering aspects.

Telemedicine services are reflected as remote connectors in diagnosis and consultation with a safer communication medium towards advanced cost-cutting and time saving [7]. The relevance of compromising medical data leads to ineffective

Table 1 Consolidated tabulation of medical image registration under MooM data processing channel of TelMED

| Images	S1	S2	S3	S4	S5	Registered Score
I1:PSNR	93.5275	78.7163	74.3594	73.4828	73.0941	78.63602
I2:PSNR	83.3306	77.762	74.4105	66.8629	79.4463	76.36246
I3:PSNR	92.987	89.1932	85.541	72.8453	68.7742	81.86814
Error Rate(R1):I1	5.63942	24.8012	38.3435	41.8563	43.5154	30.6273
Error Rate I2:R2	15.6343	27.2848	38.1482	81.1446	23.0553	22.45344
Error Rate I3:R3	5.95257	8.69896	12.5337	44.6118	67.028	15.6999
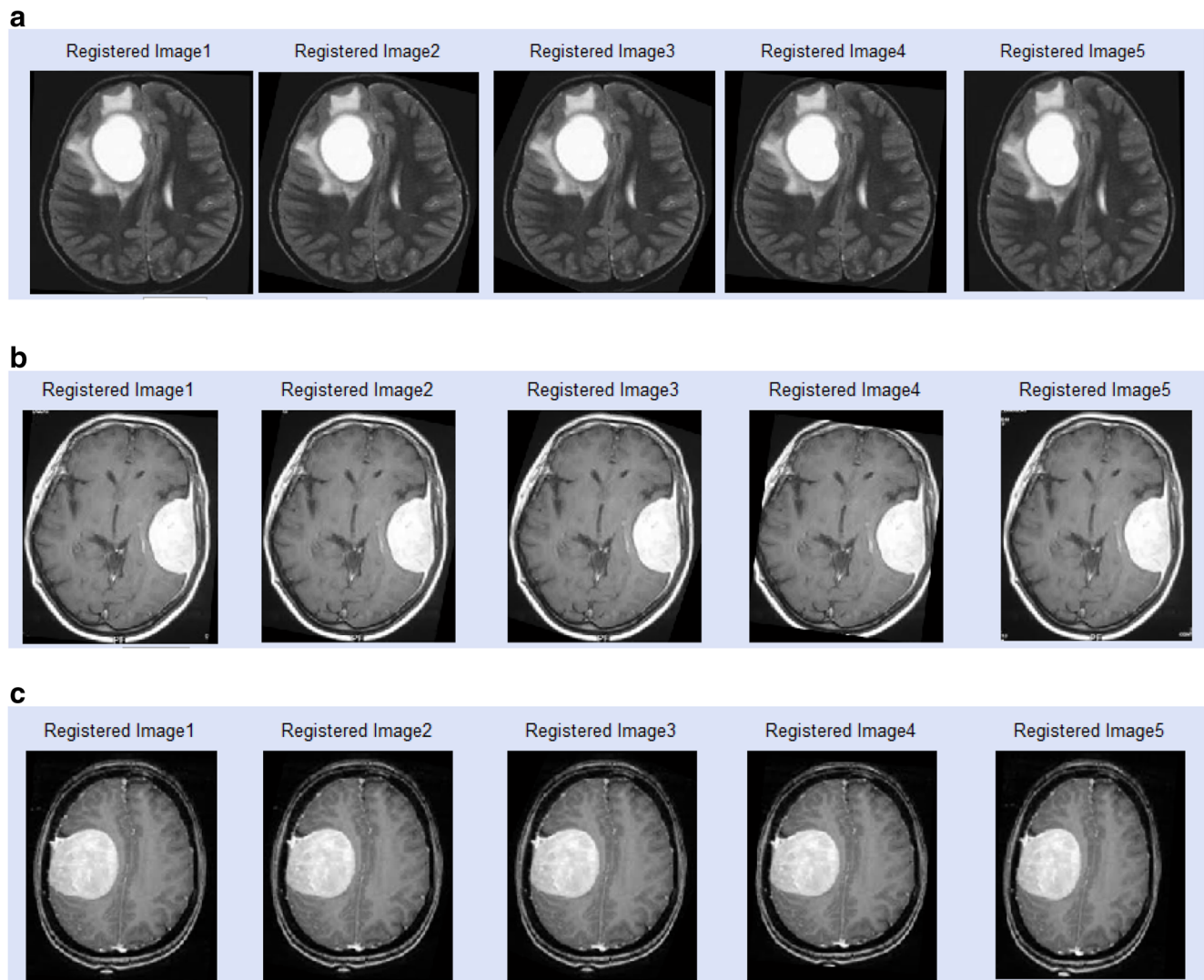
Fig. 2 a: Sample-1 of Medical image under registration b: Sample-2 of Medical image under registration c: Sample-3 of Medical image under registration

diagnosis and consultation and justifying false positive results. Thus [4, 8] revisits the deliverables of telemedicine services under rural or slighter regions [10, 12, 13].

Problem statement

Medical data transmission over current telemedicine infrastructure is performed under existing channel or spectrum with third party optimization algorithms. These algorithms reduce the reliability factor of medical diagnosis. False positive and true negative conclusions are drawn, over such interpretation datasets. Henceforth, an order of channel optimization with respect to server-end processing and reverse engineering algorithms for medical data sample is on research demand. Another major concern on dataset processing is the diversity of data-types with advancement

in technology and computation. The proposed technique is focused on MooM data-type processing inclusive of medical images such as CT/MRI/PET, medical audio signals such as ECG/Phonocardiography (PCG) and text or log data-type such as Electronics Health Records (EHR) / EEG.

Methodology

In proposed technique as shown in Fig. 1, the MooM datasets are processed with various multi-objective and multi-dimensions with respect to data-type such as medical images, audio signals samples, EHR and textural documents such as log file etc. Typically, these three forms of medical data is considered and processed. The processed data is transmitted via a designed protocol of

Fig. 3 Image registration process for recursive image detection
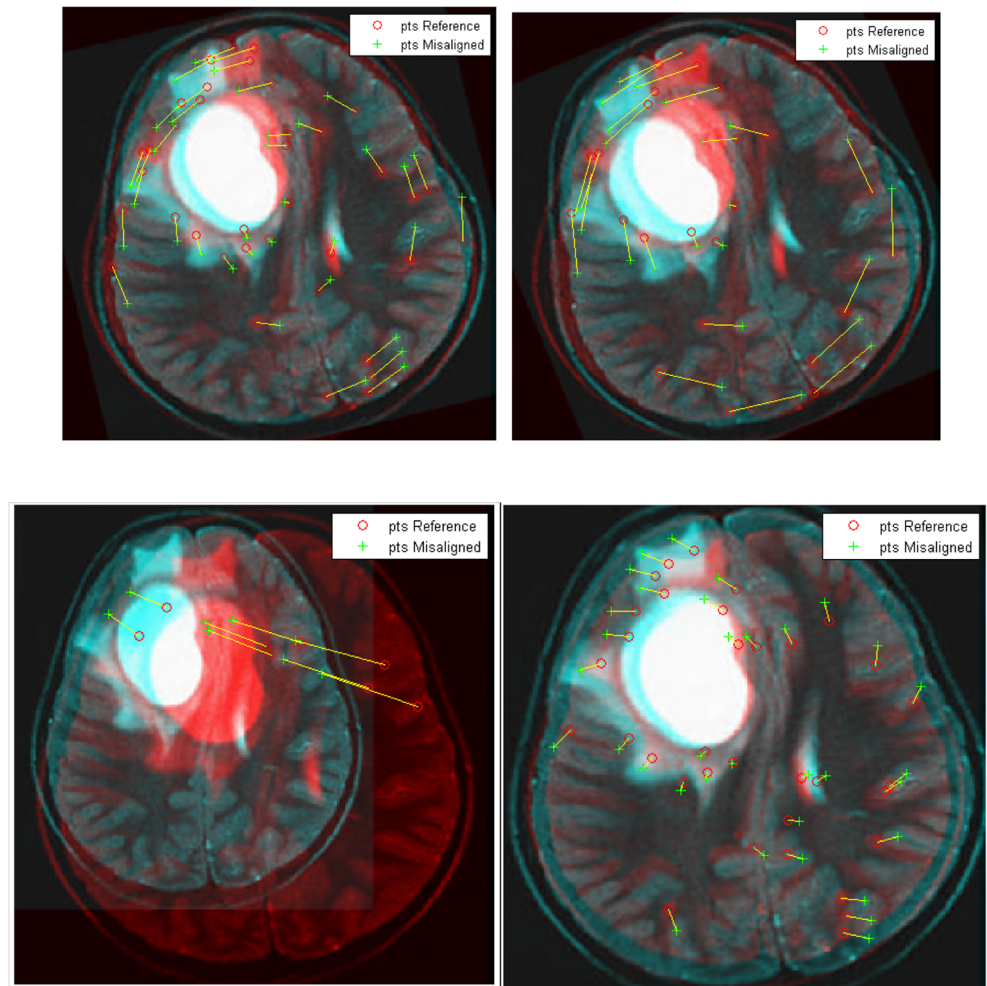
transmission namely TelMED. The protocol aims to achieve dynamic user grouping and clustering for systematic resource allocation of users over a telemedicine environment or channel of communication.

In the proposed methodology, an improvised version of MooM data processing and TelMED protocol is discussed with remote online processing schema of evaluation (i.e.) the remote users upload samples via rural center for medicine and

healthcare through a technician, the samples are future uploaded to cloud/server environment. On successful uploading, the medical datasets undergoes MooM processing. Since, the data is transmitted via a domestic channel; a third party optimization is processed. Thus the proposed system aims to perform a checksum for data uploading via TelMED infrastructure and future strengthens MooM processing for data's QoS over telemedicine channel.

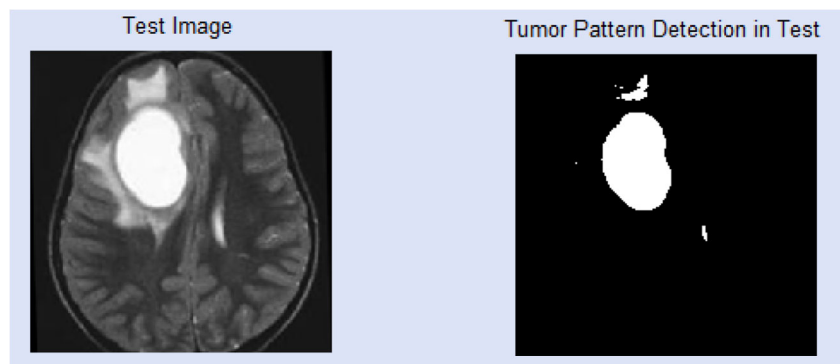**Fig. 4** Test image v/s Tumor pattern detection

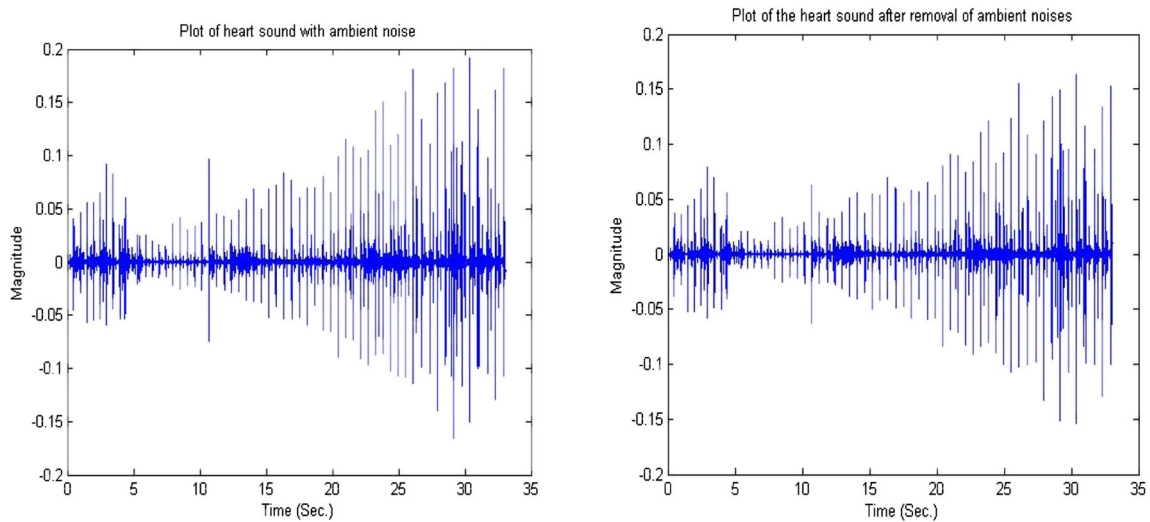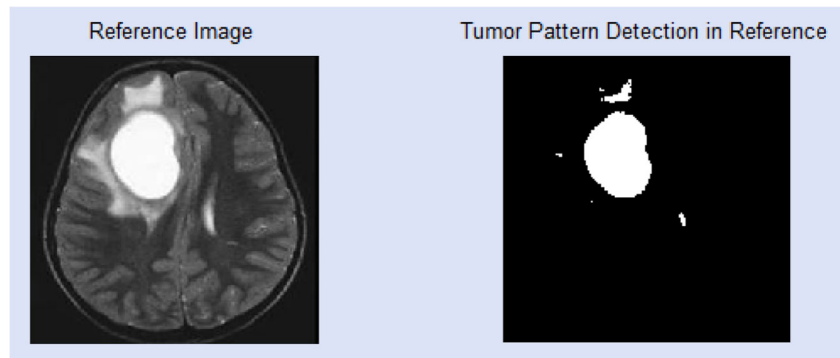**Fig. 5** Reference (Registered) Image v/s Tumor pattern detection

Fig. 6 Normal heart sound recording (Left) with noise signals (Right) on processing without noise signal

Dynamic MooM dataset processing

As discussed in previous session, the MooM datasets are processed under TelMED protocol for assuring the QoS improvisation over two ends of communication (i.e.) doctor and patients. The proposes technique is achieved with a pre-processing followed by MooM dataset oriented processing with a check-sum for measuring QoD in transmission line and cloud optimization algorithms.
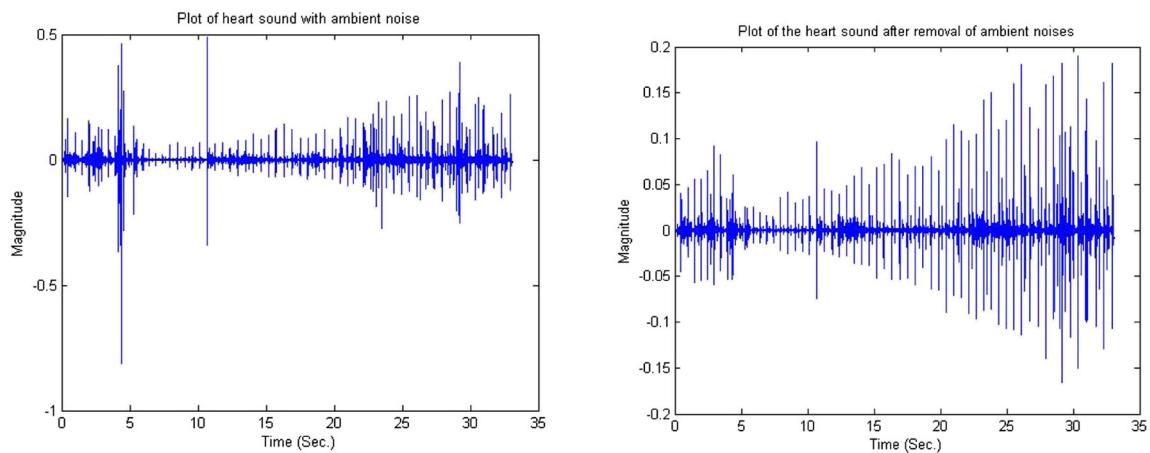

Fig. 7 Abnormal heart sound recording (Left) with Noise signals (Right) on processing without Noise signal
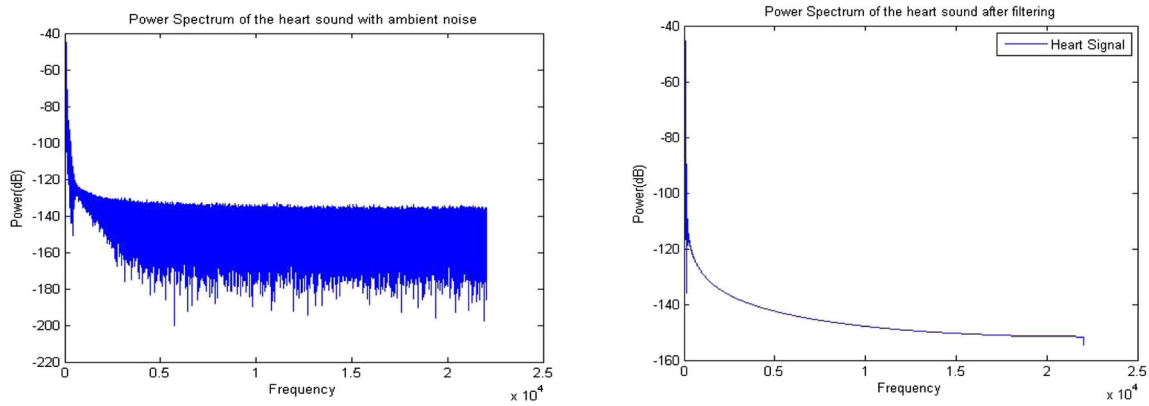
Fig. 8 Abnormal heart sound power spectrum, (Left) with Noise signals (Right) on processing without noise signal power-spectrum evaluation and sample treatment under PCG technique
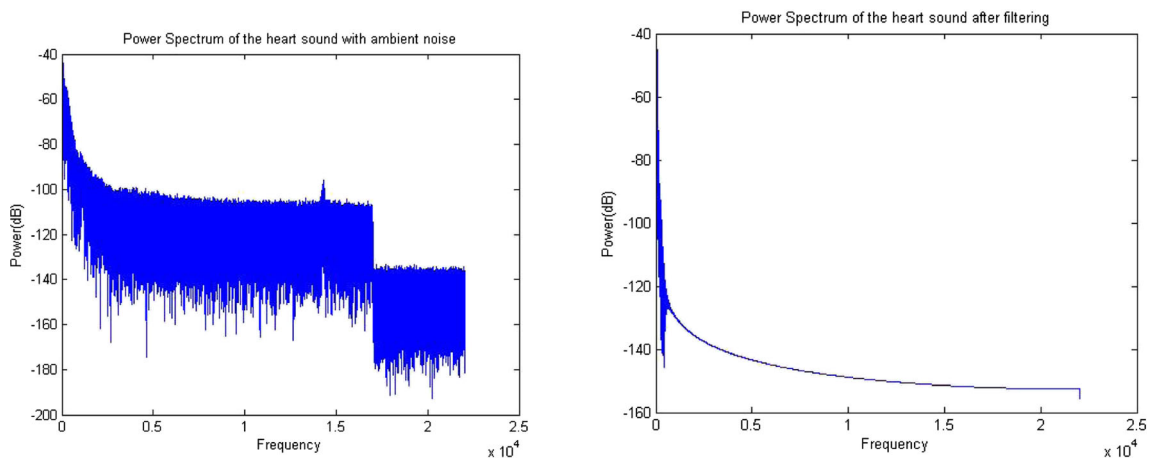

Fig. 9 Abnormal heart sound power spectrum, (Left) with Noise signals (Right) on processing without Noise signal
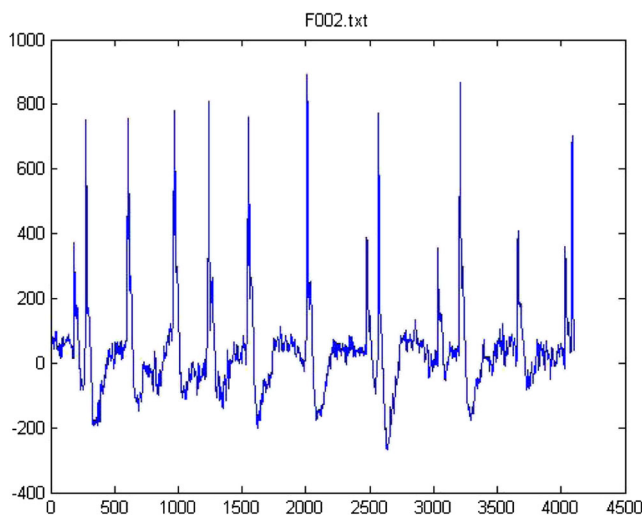

Fig. 10 Medical EEG Text data regenerated & representation for evaluation

Pre-processing of data samples

Consider a remote patient *(R)* uploading a data-sample *(D)* under a primary diagnosis for expert consultation, the data *(D)* is randomly collected via system logs of user-service provider (USP). The data is processed by a remote data collection unit designed at lowest points of healthcare and transmit via a third party network provider. Thus prior to transmission, the technician or remote care person officially segregates the data samples of TelMED.

TelMED processing

On prior to uploading, the data undergoes processing with online TelMED protocol. TelMED generates a hybrid and dynamic resource allocation and sharing technique for establishing a secure and reliable connection for transmission.
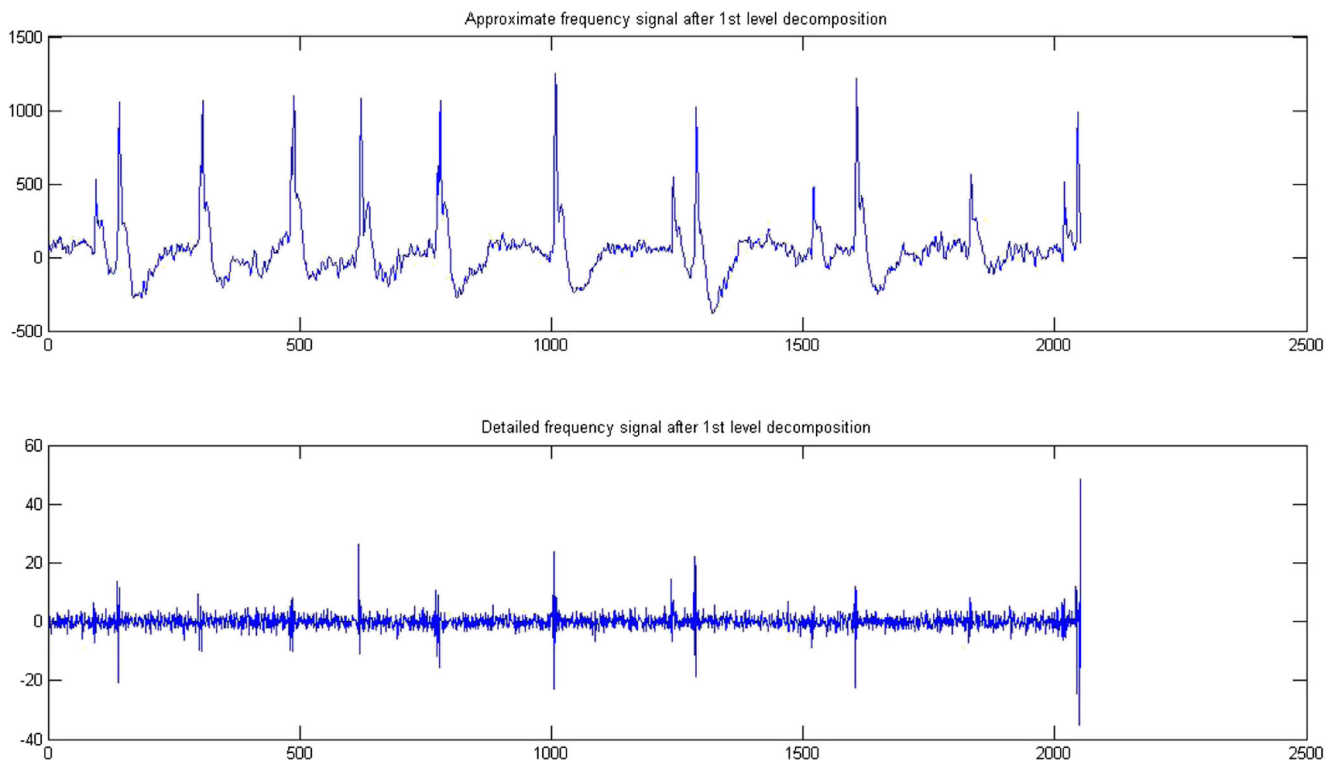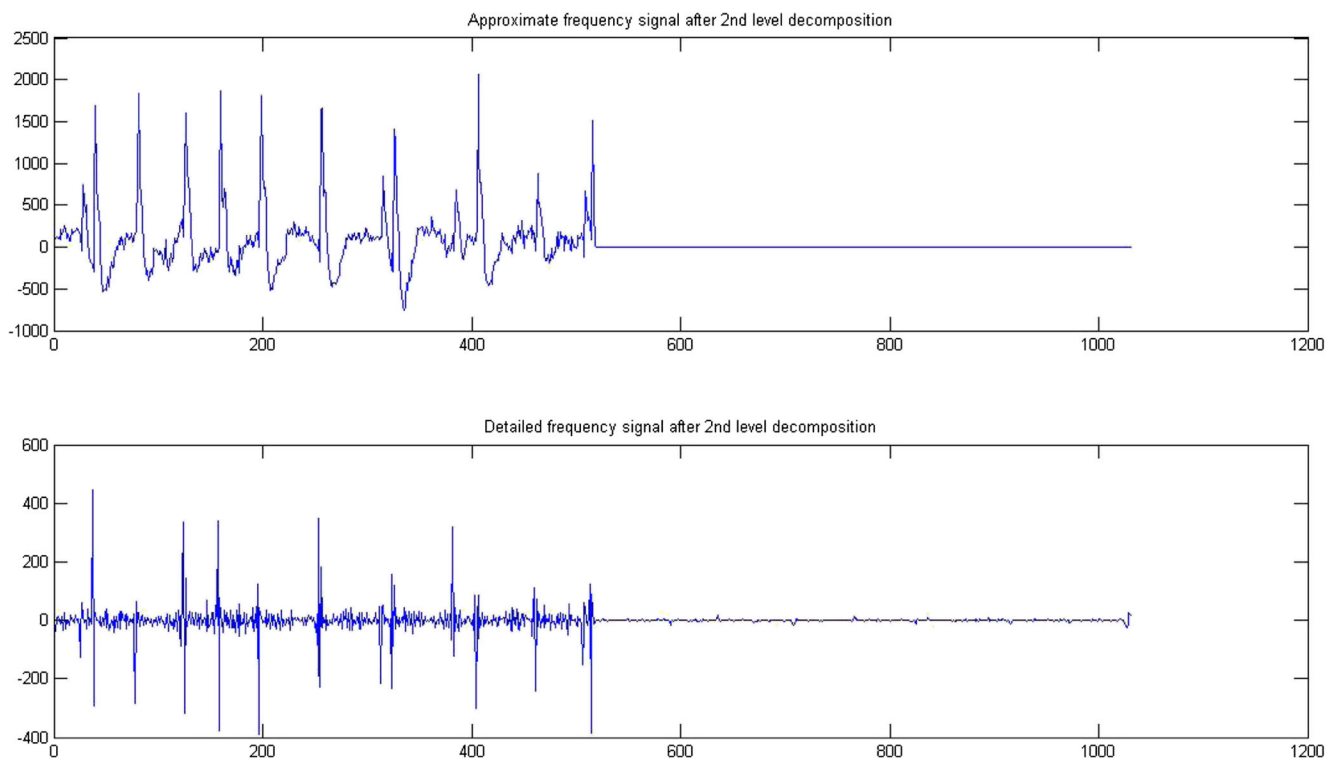
Fig. 11 Data filtering under 1st level of decomposition

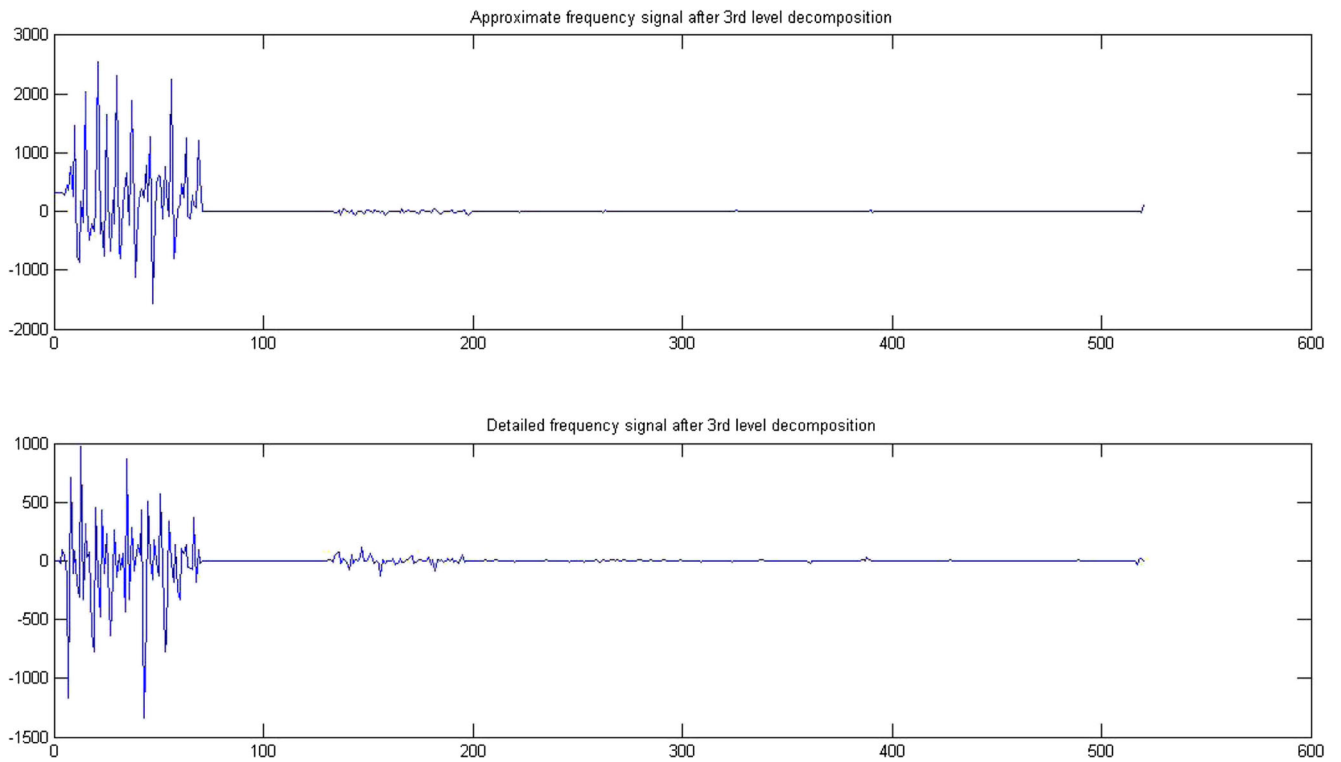**Fig. 12** Data filtering under 2nd level of decomposition

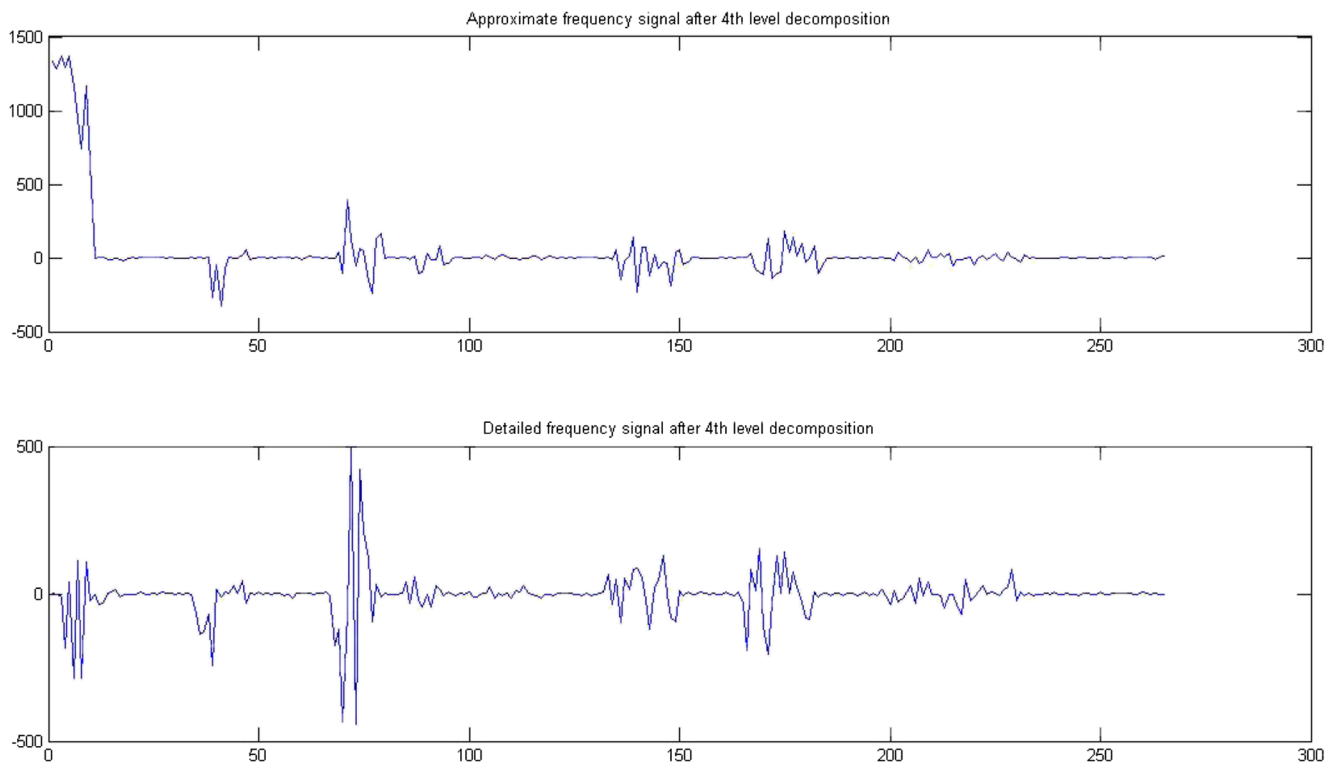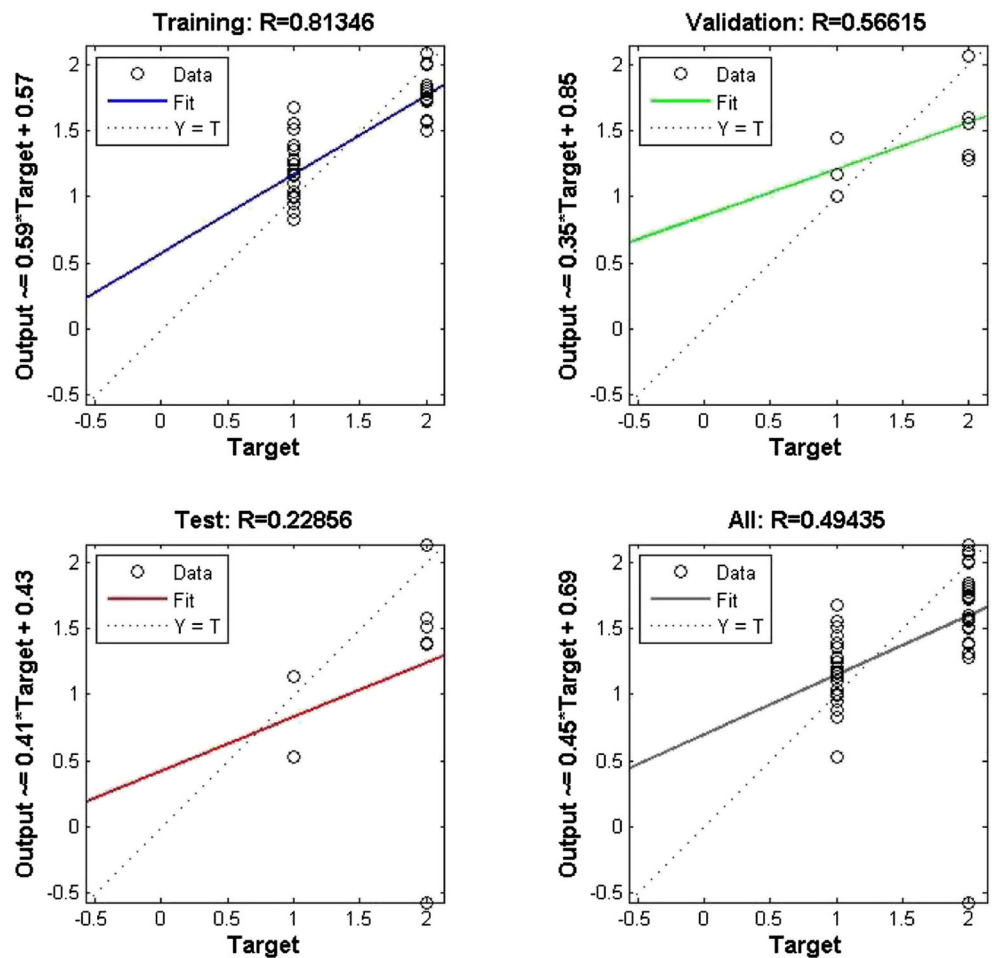**Fig. 13** Data filtering under 3rd level of decomposition

Fig. 14 Data filtering under 4th level of decomposition

Fig. 15 Validated results under machine learning processed of evaluation [9]

Consider, the given dataset *(D)* is uplifted for transmission under TelMED protocol infrastructure; typically TelMED is designed on dynamic Multiple Input Multiple Output (MIMO) based user clustering and classification framework. Hence represented in a hexagonal format of cells-creation. The dynamic user grouping (DUG) algorithm can be represented as in Eq. 1

$$S(u) = \left[\lambda_T . U_T . \sum_{i-0}^{n} \frac{\delta(H_i)}{\delta t} \right] \qquad (1)$$

Where, U_T is user group under transmission of bandwidth (λ) for a time interval *(T)* with H_i representing hexagonal cell alignment with respect to interval of time *(t)*. On a summary the overall TelMED framework can be represented as

$$\phi(T_A) = \frac{1}{t} \int_0^R \left\{ \lim_{\delta t \to 0} \left[\log_E . \frac{\delta(e^S)}{\delta R} \right] \right\} \qquad (2)$$

Such that, the data uploaded to the server is co-related and formulated with an improvised and optimized techniques for uploading under TelMED scheme, the medical data processed is secure and reliable for future optimization under third party

algorithms and hence generates a dynamic strategies towards data preservation on open channel of communication.

Medical dataset processing on MooM data-samples

Pre-processing and indexing

Telemedicine datasets are sensitive and are exposed to various third party optimization algorithms and challenges such as bandwidth, multiple data uploading, multiple times similar data uploading and manual errors. Typically these errors or challenges causes image or data recursion and improves duplication and data manipulation scenarios. Thus, in the proposed technique, a dedicated recession algorithm is proposed and validated using machine learning terminologies *(KNN)* for upgrading a better result under remote diagnosis channel. The source data collection varies from one server to another host respectively. Consider a data sample *(I)* with an unique features recorded under database model and thus repeated version of same is searched or validated, thus representing each of data-sample of given server as $I = \{I_1, I_2, I_3...I_n\}$ where *'n'* is the dynamic value of medical samples indexing for given server based on uploading standards [11].

Consider a scenario; there exists a medical sample I_f on an occurrence against a location L_f for independent addresses i.e. $I_f \subseteq I$ such that, each of I is against L and $L_f \subseteq L_n \in L$ where each of L is a memory location on indexing a sample. This reflects overall system for recurrence detection and elimination. Thus represent in eq. 3

$$R = \int_0^L \left[\sum_{i=o}^n \frac{\delta(I_i)}{\delta t} \right] . \Delta x \qquad (3)$$

Medical image interpretation on optimized data

In previous section, a recursive medical data samples are extracted and redefined set *(R)* is retrieved for a given transaction over a remote network. The successive step is to define and validate the images with re-alignment of mis-lead angular differences such as images with varying angles of freezing. Such images are not detected using pre-processing and indexing techniques. Since a relative edge detection and pixel density based variation methods are appended, the registration technique demonstrates a higher order of reliability and accuracy.

Consider the secondary processing images (I_S) over the set of defined and pre-processed set *(R)* such that, each of $(I_S \subseteq R)/R \subseteq I_f \in I$. The interdependency of each image (I_S) is fetched from user *(U)* transaction. Assume *k* images are processed from *(R)*, and then the region of extraction of cover image / reference image to that of *k* images is given in Eq. 4

$$S = \int_0^{I_S} \sum_{i=0}^k \left[\frac{\delta(S_i)}{\delta t} \right] \qquad (4)$$

Where, S is the set of registration images logs to that of k iterations resulting in repeated iteration as $S = \{S_1, S_2, S_3...S_n\}$. For each of $S \in R \Rightarrow k \subseteq I_S$ on comparison with reference images (R_S), the S should generate an equivalent ratio of minimal errors and maximum similarity as in Eq. 5

$$D = \left[S - \left(\frac{\delta(R_S)}{\delta t} \right) \right] \cong 0.7270 \qquad (5)$$

For each iteration of image, a consolidated generation of optimized set is represented, such that, the consolidated data on processing is equivalent to the data over a channel. Thus the retrieved images processes a cancer lesion detection on a generalized and optimized set of data using open third party algorithms with a synchronization as shown in Eq. 6

$$S_I = \frac{1}{2\pi} \left[\int_{-\infty}^\infty \sum_{i=1}^t \left\{ \frac{\delta(D_i)}{\delta t} . (H_D)_i \right\} \right] \qquad (6)$$

Where, *D* is the consolidated set of data representation over H_D (Huffman's distribution) for optimized images. Thus the tumor in sample with a pattern density *(x)* over Eq. 3 is fetched on a difference with Reference image R_S.

Medical signal interpretation on optimized data

Medical signals are compressed on interpretable audio signals *(*.wav)* and sensitive audio recordings of internal organs. In MooM, a series of representation is demonstrated over a Phonocardiography (PCG) and Electrocardiography (ECG) signals and fetched a frame of data over a low line channel of communication as represented in Eq. 7

$$S_A = \frac{leng(P_S)_i}{2\pi} \left[\int_{-\infty}^\infty \sum_{i=1}^t \left\{ \frac{\delta(P_i)}{\delta t} . (\mu)_i . P_{(S)_i} \right\} \right] \qquad (7)$$

Where, (P_S) is considered as feeder signal for communication over low line channel and is computed on length of signal to that of each signal is internally segregated and framed as MOTIF units of smaller representation. Further, in proposed scheme the validation of Eq. 7 is pre-moved on cloud/server environment towards quality assurance under third party optimization algorithms. The incoming signal S_A is received and broken down into secondary units of data in expanding MOTIF signal *(M)* as in Eq. 8

$$\int_0^{S_a} M = \lim_{n\to\infty} \int_{-\infty}^\infty \left[\sum_{i=0}^n f(P_i) \Delta(x_i) \right] \qquad (8)$$

Where, each of signal's expanded unit is explored with respective to MOTIF data on a internal ratio of saturation $\Delta(x_i)$ occurred in each Motif pattern *(M)* i.e. $M = \{M_1, M_2, M_3...M_{Sa}\}$ where $M \subseteq S_a$. Typically, Motif *(M)* is extracted from series as shown below

$$M = \int_{-\infty}^\infty \left(\frac{\delta(P_A)}{\delta t} \right) * leng(P) \qquad (9)$$

Where $\forall P_A = \{P_{A1}, P_{A2}, P_{A3}....P_{An}\}$ represents a generalized form of $\sum_{i=0}^n (P_A)_i$ with each signal portion describing an attribute as in Eq. 10

$$S_A = \int_{-\infty}^\infty \ln \left(\frac{d\left[\sum_{i=0}^n (P_A)_i \right]}{dt} \right) leng(P_A) \qquad (10)$$

$$\therefore S_A = \int_{-\infty}^\infty \ln \sum_{i=0}^n \left\{ \left(\frac{d[(P_A)_i]}{dt} \right) leng(P_A) \right\} \qquad (11)$$

Thus from eq. 11, an inter connective expansion of signal is achieved at receiver end and expands (P_A) to original form of S_A with $leng(P_A)$. Thus, to validate the given signal quality, integrated quality variables is attested with extracted quality variables on sever-end. Framing a loop-up look-up circuit for QoS enhancement as demonstrated below.

Medical text-records interpretation on optimized data

The other common form of medical data representation is textural or text format, such as data files, Comma Separated Value (CSV) files, EHR and PDF based on EEG data logs files etc. Typically, the data in this modern era of technology deals with larger files on continues value extraction and hidden patterns or information mining. In the proposed terminology, the data files are correlated and processed with machine learning based KNN approach for clustering and validating the most relevant information segment from considered file.

Typically, a file (F_S) is considered with EEG log information, such that each of (F_S) is segment under optimization algorithm as $F_S = \{(F_S)_1, (F_S)_2, (F_S)_3 \dots (F_S)_n\}$ with n^{th} segment to the highest order of file division. According to generalized terminology of KNN, a nearest neighbor is appended for clustering as follows.

$$C = \frac{^*EoF}{2\pi} \left[\frac{\partial(F_S)}{\partial(S)} \right] \qquad (12)$$

$$i.e. C = \frac{^*EoF}{2\pi} \left[\sum_{i=0}^{n} \sum_{j=0}^{k} \left\{ \frac{\partial(F_S)_i}{\partial(S)_j} \right\} \right] \qquad (13)$$

Where, each of file recorded a End of File (EoF) operation pointer and file segments with S_K intervals. i.e. $S_K \leq {}^*EoF \Rightarrow (F_S) \subseteq F$ as F is the unprocessed file of medical data and F_S is the processed file on low line third party channel of communication. Thus on expansion, the QoS of each segment of file is evaluated and compered to F_S with respect to F. such that, $(F_S \approx F) \leq (0.732/2\pi)$ where, the value is equivalent to received F. For optimized transaction i.e. $C = \{C_1, C_2, C_3 \dots C_n\}$ and hence, clustered data, re-building of F_S on experimental environment is evaluated as Eq. 14

$$F_S = \frac{^*EoF}{2\pi} \left(\lim_{0 \to 0} \left[\sum_{i=0}^{n} f(C_i) \right] \Delta P_i \right) \qquad (14)$$

On reverse engineering of optimized or clustered data (C_i) a reassembling of original or alike original file (F) is retrieved from F_S. On experimental consideration, EEG based RT-BIRD algorithm is proposed for optimization and retrieving extraction.

Discussion and results

The proposed methodology is to implement an optimized data processing using trivial technique on machine learning to retrieve originality behavior of master file/record. In the proposed system a detailed study is evaluated on various file system on architecture of TelMED protocol to retrieve MooM datasets. Over a low band communication channel and third party optimization. Firstly the medical images are retrieved with better QoS and are tabulated in Table 1 for higher order of registration and rebuilding.

Processing of medical image samples

In Fig. 2a, b and c a descriptive imaging of reference images of each five (5) sub-samples are considered for registration and Fig. 3 demonstrates, the registration processes involved for image aligning and point coordinating to retrieve best similar image root. Thus on appending, the results towards third party or generalized [4] technique of image processing, the detection of tumor accuracy is likely to be on distortion rate of 2.456. (i.e) the resemblance is 97.5% on an average for consider data-samples (Figs. 4 and 5).

Processing of medical signal samples

Medical signal data samples include a Phonocardiography (PCG) signal processing, acquired via nodal head-phones of range 0-250KHz as demonstrated in Figs. 6 and 7 respectively. Figure 6 demonstrate normal signal processing of heart samples acquired via PCG technique and hardware setup and Fig. 7, represents an abnormal acquired signal.

Processing of medical text/log file samples

Medical data is represented in most common form of text and electronics health records. Hence forth, the data considered for evaluation is sampled from various EEG log records and are structured to perform a represented pattern of data as in Fig. 8. Thus, it represents a virtual signal regeneration pattern for physical data under logical format of evaluation (Figs. 9, 10, 11, 12, 13, 14 and 15) [9].

Conclusion

Telemedicine is next generation terminology of communication with enhancing e-health and modernization with medical instrumentation. The proposed technique is focused with medical data regeneration and interpretation with respect to third party optimization algorithms and low line channel of transmission. The technique is focused with dynamic processing via TelMED protocol and reterives Multi-Objective

Optimized Medical (MooM) data-types. Typically, MooM data-types are processed for first time under collectively processed and single platform with a run-time environment.

The proposed technique aims to improvise Quality of Service (QoS) and Quality of Data (QoD), under supervision of machine learning algorithms. The technique has successfully processed and synchronized a higher-order of QoS and QoD for various MooM data-types such as Images (CT/PET/ MRI), audio (PCG/ECG) and text/log files (EHR/EEG) with a demonstrated performance on third party optimized data. In near future, the technique can be improvised with added and expanded MooM data-types such as 3D imaginaries, Ultra-graphic records, nano-scale imaginaries and much more in an explore manner.

Compliance with Ethical Standards

Ethical Approval   This article does not contain any studies with human participants or animal performed by any of the authors.

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