ISSN: 0976-9102 (ONLINE)
DOI: 10.21917/ijivp.2021.0349



# DESIGN AND DEVELOPMENT OF VIBROARTHOGRAM SCREENING DEVICE AND ASSESSMENT OF JOINT MOTION IN THE PURSUIT OF SIGNAL PROCESSING

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***Abstract***

***Abnormal conditions in the knee joint are factors to lead changes in the vibroarthro graphic signal which represents the sound or vibration emitted from the joint during flexion or extension with suitable instrumentation these signals are to be acquired and also converted into digital signal. Signals are amplitude limited, distorted limited length and non-stationary in nature. The vibroarthro graphic system is unknown, modeling of vibroarthro graphic signal are essential to explore physiological behavior. Biosignal Processing and Pattern classification techniques have been applied to vibroarthro graphic signals to derive features that characterize the state of articular cartilage surface and assist in non-invasive detection of knee joint pathology. Screening of knee joint abnormal condition using vibroarthro graphic signals could reduce the need for diagnostic surgery. Diagnostic surgeries are invasive techniques and could deteriorate joints as well. In the first part of the work suitable instrumentation setup is designed and developed. Subsequent second part of work is extended to model vibroarthro graphic signal and algorithms are used to assess joint motion in the pursuit of signal processing.***

***Keywords:***

***Instrumentation Amplifier, EMG signal, Vibroarthrogram, Modeling, Signal Processing***

## 1. INTRODUCTION

Joint pain and arthritis is one of the common age related problem affected by aged regardless of gender or ethnic group. According WHO report the prevalence of disease is about 1-5% in developed countries. Women population is prone to disabling condition [1]. Interpretation of non-stationary VAG signals is segmented locally stationary and adaptive filtering algorithm is used to segment for further processing [2]. Electromyography is the study of the electrical activity of muscle. Electromyography provides important information on the physiological status of skeletal muscle and nerve. In cases of muscle paralysis or related muscle, it allows identification of the damage, within the brain or spinal cord its axon, the end plate, and muscle fibres. A normally innervated muscle shows no electrical activity at rest; when voluntarily or reflex contracted it produces action potentials. The individual muscle fibres start to contract and relax independently. Random and asynchronous contractions produce no net muscle tension, and they continue as long as there is muscle tissue present [3].

### 1.1 KNEE JOINT

The human knee joint is the most complex and the largest joint structures in human body which it is surrounded by numerous of ligaments and tendons known as synovial joint as it contains synovial lubricating fluid. Patella is a protector from external injury. Ligaments will be supporters and provides stability. Lateral and medial collateral ligaments, anterior and posterior cruciate ligaments are the stabilizers by giving support to the knee.

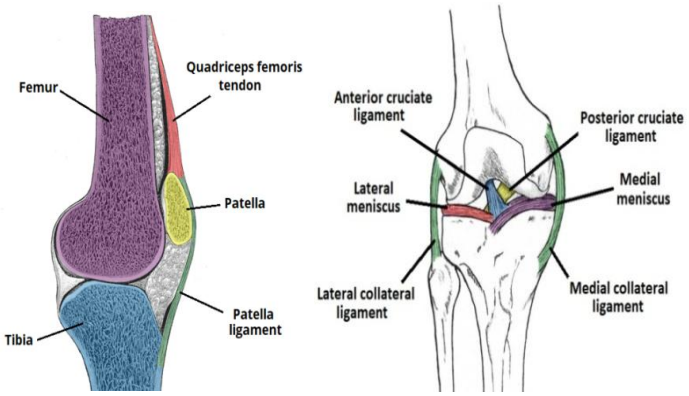


Fig.1.The structures of Knee joint: femur, tibia and patella and important ligaments [3]

The knee joint is a hinged attachment to synovial joint, which mainly permit for extension and flexion (and a small degree of medial and lateral rotation). It is formed by the articulations intermediate the patella, femur and tibia. The Fig.1 shows the knee joint anatomy. It is a complex structure have its articulating surfaces, ligaments and neurovascular supply.

- **Articulating Surfaces**: The structures knee articulating surfaces have two articulations called as tibiofemoral and patellafemoral. The surfaces are line by cartilage, hyaline.
- **Neurovasculature**: Surrounding the knee, blood supply to the knee joint is done through the genicular anastomoses; this blood supply will be done by the genicular branches of the femoral and popliteal arteries. The muscles which cross the joint with the supply are through the nerve connection. These are the tibial, femoral and fibular nerves.
- **Menisci**: The lateral menisci and medial are fibro cartilage components in the knee which is used for two major roles: It will increase the stability when the articular surface of the tibia gets deepened. It will act as shock absorbers by increasing surface area to further dissipate forces (damping vibrations).
- **Bursae**: A bursa is a sac filled by synovial fluid, can be seen in moving structures of joint – with the aim of lowering wear and tear. Synovial fluid filled sac is of four types in the knee joint. These are names such as: i) the extension of the synovial cavity of the knee is Suprapatella bursa, the quadriceps femoris and the femur will located and mediated.

ii) Prepatella bursa is seen intact with the apex of the patella and the skin. Infrapatella bursa is separated into two type superficial and deep, iii) the tibia and the patella ligament will have the deep bursa in between. The superficial lies between the patella ligament and the skin and iv) between the semimembranosus muscle and the medial head of the gastrocnemius will have the Semimembranosus bursa (Located posterior in the knee joint) in between.

- **Ligaments**: The major ligaments in the knee joint are:

1) Patellar ligament is the continuation of the quadriceps femoris tendon distal to the patella. It attaches to the tibial tuberosity.
2) Collateral ligaments contain two strap-like ligaments. It will act as the stabilization to the hinge motion of the knee, by preventing the lateral movement or excessive medial.
3) Tibial (medial) collateral ligament have the wide and flat ligament, which was found on the medial side of the joint. It attaches to the medial epicondyle of the femur - Proximally, it attaches to the medial condyle of the tibia - distally.
4) Fibular (lateral) collateral ligament is rounder and thinner than the tibial collateral, it is attached proximally to the lateral epicondyle of the femur, and it is attached distally to the depression on the lateral surface of the fibular head.
5) Cruciate Ligaments has two ligaments connect, the tibia and the femur. In this case, they cross each other, hence the term 'cruciate' (Latin for like a cross) has been termed. At the anterior intercondylar region of the tibia anterior cruciate ligament is attached where it blends with the medial meniscus. It ascends posterior to attach to the femur in the intercondylar fossa. It prevents anterior dislocation of the tibia onto the femur. At the posterior intercondylar region of the tibia posterior cruciate ligament is attached, and ascends interiorly to attach to the anteromedial femoral condyle. Posterior dislocation of the tibia onto the femurusis prevented.

- **Movements**: The knee joint permits with four main movements

1) ***Extension***: Inserts into the tibial tuberosity which is produced by the quadriceps femoris,
2) ***Flexion***: Produced by the gracilis, hamstrings, popliteusandsartorius
3) ***Lateral rotation*** is produced by the biceps femoris and
4) ***Medial rotation*** is produced by five muscles; Sartorius, gracilis, semitendinosus, semimembranosus and poplite.

- **Factors to Study**: i) ageing ii) injury iii) trauma iv) degeneration v) exploitation
- **Vag Potential**: The knee joint generates vibration signal and could be used to detect early stage knee joint pathologies. The method of detecting the vibration signal to diagnose injury is known as vibration arthography or vibroarthograpy (VAG).
- **Signal Processing**: In this system speaker is provided for auditory monitoring. The diagnostic information is in form of waveform and repetition rate. With the experience, the ear can be detecting normal motor unit action potentials, Potentials give a ticking, clicking, or crackling sound. It is to recognize these and other characteristic waveforms after skill and experience.

The next section provides discussion about the work carried out by previous researchers in the detection and prediction of knee joint assessment.

## 2. BACKGROUND OF STUDY

In [7] Adaptive segmentation method entrenched on the recursive least squares lattice (RLSL) algorithm was evolved. The Auto regressive (AR) modeling method was changed method for adaptive cancellation of muscle contraction interference was firmed and classified of Knee joints was conveyed into two groups and six groups. The kinematics of shoulder motion together with the upper trapezius and serratus anterior muscle activation in violin musicians are evaluated by using a Spotted and valid kinematic and EMG data reduction techniques [10].

Interpretation of non-stationary VAG signals is segmented locally stationary and adaptive filtering algorithm is used to segment for further processing [2]. Study carried by Nalband et al. ,stated in their study the intensity of disease has been projected 65 million case by 2025 [8].Disorder affecting a variety of physical functions which afflicts and impose restrictions on the patients' daily life. Thus automatic detection and prediction of disability is of great importance. Over last two decades many diagnostic measure and few prediction methods have been developed using EMG and VAG signals. The Table.1 contains the important literature available for the methods of automatic detection and prediction of pathological conditions.

Table.1. Information from literature

| Authors | Type of Study | Tools Used and Method | Result | Contribution |
|---|---|---|---|---|
| Rangayyan, R.M et al. [4] [5] | VAG signal acquisition and process | Fourier, Time and frequency domain | Understanding physiology behind knee joint | Insight into the bio signal applications |
| Rangayyan, R.M et al. [6] | Non linear | Fractal dimension | Understanding physiology behind knee joint | Non-linear analysis of physiological process signal in perception of modeling |
| Y. Wu et al. [5] [6] [13] | Features | Radial basis function, Artificial Neural network (ANN). | Distinguishing normal and abnormal signals | Classification |
| Nalband et al. [8] | Classification | Modeling and pattern classification | Analysis | Classification |
| Dawid Bdczkowicz et al. [11] | Statistical | Time-frequency analysis | Trend analysis in age related subjects analyzed | Diagnosing age related impairment |

The Spectral analysis is the most familiar quantitative linear method available for the analysis of VAG signals. The frequency spectrum of the signal is obtained by using Fast Fourier

Transform (FFT) to VAG signals. Frequency domain approach has reached importance as a detection diagnostic tool. Bio signals are non-stationary in nature sometimes analyzing these signals using linear method will not results in good performance measures, keeping these facts using nonlinear method certainly result in improved detection accuracy and performance measures [6].

From the above literature survey it is inferred that researchers have been used different discriminative features among various phases in VAG forms basis for proposed method. Hence literature is available on feature selection and automated classifications are also presented.

## 3. MATERIALS AND METHODS

### 3.1 SUBJECT AND INFORMATION ABOUT THE DATA

We worked with dataset contains 89 vibroarthrographic signals (VAG or knee-joint sound signals) recorded from 51 normal subjects (novag**) with no knee-joint pathology and 38 subjects with various types of knee-joint pathology (abvag**) [6]. Out of 24 subjects each normal (VAG or knee- joint sound signals) and with various types of knee-joint pathology (abnormal) signals are chosen for analysis.

All signals are sampled at 2000 samples per second, data recorded 2-5 second duration. From this set, 24 segments of normal VAG are considered as healthy knee conditions and 24 segments of pathological data considered as diseased for the present work. Permission is granted for use of the data for academic and research. The features corresponding to normal and abnormal conditions are computed for Dataset. Permission is granted for use of the data for research and academic purposes from the dataset repository made available [4], [13].This work is simulated by Matlab software.

### 3.2 DESIGN AND DEVELOPMENT OF INSTRUMENTATION AMPLIFIER

The main section of this research article is based on methods are described to instrumentation setup to assess condition. In this work, VAG recording is used to determine any abnormality and identification of parameters leading to automatic detection.

#### *3.2.1 Recording of Vag Signals:*

Sensors, audio microphone, thin film accelerometer, piezoelectric are tested. The instrumentation amplifier with electrical isolation and 50 Hz notch filter existing laboratory setup has been used to acquire signal. Sensors are to be placed on the tibia 10 cm from the distal knee joint space to obtain analogue vibroarthrographic (VAG) signals sampled at 2000 Hz. A band pass filter is used to pass signal frequency from 10 to 1000 Hz to avoid muscle artifact (wandering). A task was started knee joint flexion and extension recorded for 2-5s. The analog VAG signals were translated to digital data using an AD converter (Power Lab AD Instruments) and National Instruments (NI -USB 6009 low cost ADC) has been tested. Meantime during present pandemic crisis, to proceed further with the real time data and testing is not possible. Realizing that, we proceeded with data available in web resources. Testing of real time data with present available facility utilized some extent for limited (voluntary individuals) clinical subjects. Ethical clearance and clinical trials are kept open option in future scope. Teague et al. [14] extensive work carried and succeeded to acquire good quality signal. They have been tested with different types of sensors and reported in their research paper higher quality signals are obtained with air microphones [14]. To ameliorate the classification performance, the novel classifier fusion system based on the dynamic weighted fusion (DWF) method is used [12]. The Fig.2 showing sensors available for recording VAG signals.

Fig.2. Proposed sensors and transducer [14] [3] [9]

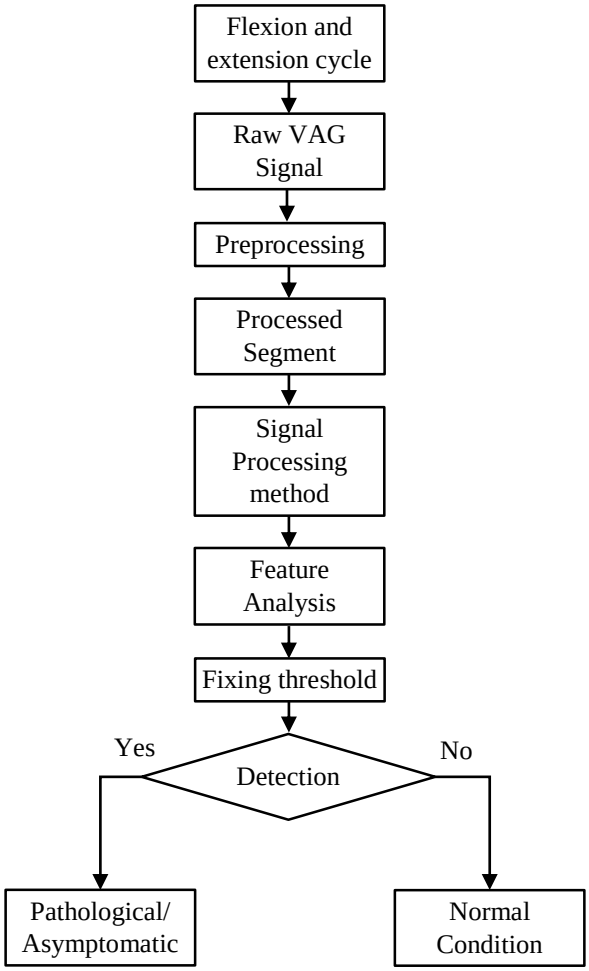


Fig.3. Flow chart of proposed method

#### *3.2.2 Method For VAG Processing:*

The Fig.3 shows the flowchart of proposed algorithm. The VAG data from the dataset is required to preprocess earlier to apply signal processing methods.

## 3.3 MODELING AND SIGNAL PROCESSING METHOD

In this method, spectral power is used as a key feature to detect signal feature. Autoregressive (AR) technique is used to compute the spectral power.

### *3.3.1 Description of the Data:*

Dataset are publicly available; the set of VAG data for analysis in this work are obtained from the database made available by Centre at the University of Calgary and made available in website (http://people.ucalgary.ca/~ranga/enel563/SIGNALDATAFILES//) For the present study, from this dataset, two sets of VAG, namely normal subjects and patients with knee-joint pathology each containing (normal and abnormal signal) VAG segments each of in seconds duration with a sampling rate of 2000 Hz, are considered. The subjects are provided vocal prompt to complete the flexion and extension cycle in few seconds which is approximately 2-5 seconds duration. The VAG segments are chosen for detection and analysis. Exemplary recordings of normal and pathologic signal (asymptomatic) that is abnormal VAG segments of 4 seconds duration from Dataset are given in Fig.4 (a) and Fig.4 (b) respectively.

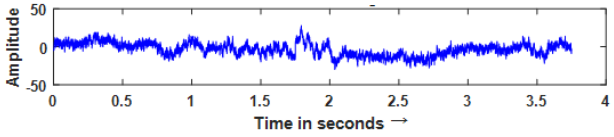


Fig.4(a). Normal VAG signal

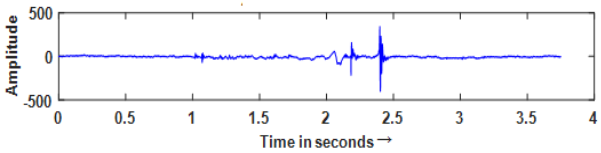


Fig.4(b). Abnormal VAG signal

## 3.4 EXPERIMENTAL WORK AND DISCUSSIONS

Modeling of biosignal is one such significant approach. VAG signal characteristics are known to be from 10 Hz to 1000 Hz. Amplitude is depending on the amplifier gain setting. Removal of noise, artifacts, baseline corrections and normalization process are made as per conventional signal processing. Presently proposed method is based on signal statistics such as linear method (variation in time and frequency). Finding its fractal dimension (FD) of the segment using nonlinear method too. Then the signal amplitude is quantified to one. The VAG signal is filtered using a digital band pass finite impulse response (FIR) filter with Hamming window technique to remove out-of-band noise. The order of the filter is 40 and cut off frequency is 10-1000 Hz, covering almost significant VAG band. The Fig.4(a) and Fig.4(b) show the results of processing a VAG epoch for normal knee joint movement and ailment condition abnormal epoch segments respectively. The Fig.5(a) and Fig.5(b) show autoregressive (AR) modeling (Burg) power spectrum.

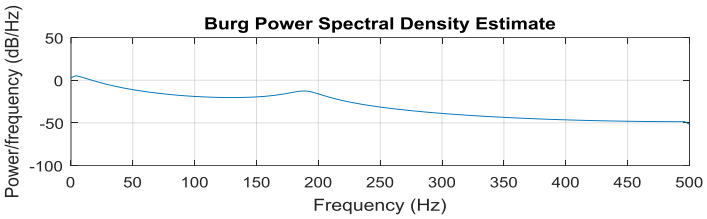


Fig.5(a). Normal VAG signal spectrum

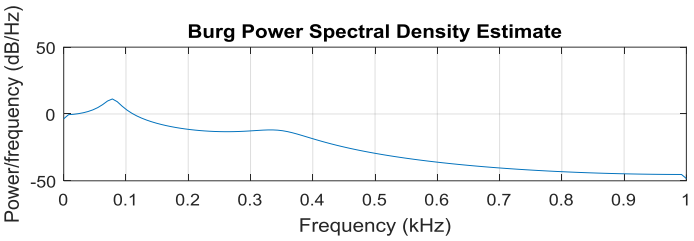


Fig.5(b). Abnormal VAG signal spectrum

From the dataset mentioned above 25 normal and 25 abnormal signals are analyzed. It has been observed notable spectral feature maximum power in dB at frequency evolved as discriminating feature.

The Fig.6(a) and Fig.6(b) shows the spectral power values for normal VAG and abnormal VAG segments. Computation of averaged signal power shows detection results. Comparing Fig.4(a) and its power distribution depicted in Fig.6(a) are smoothed. In contrast with abnormal VAG signal referring to Fig.4 (b) and subsequent averaged power distribution in Fig.6 (b). It can be seen that at time signal 2.5 second (Fig.4(b)) and power level almost coincides maximum level up to 22.91 dB (Fig.6(b) shown in window box). In order to understand characteristics, absolute magnitude of (averaged) power level (amplifier gain) in dB calculated and illustrated in figures below.

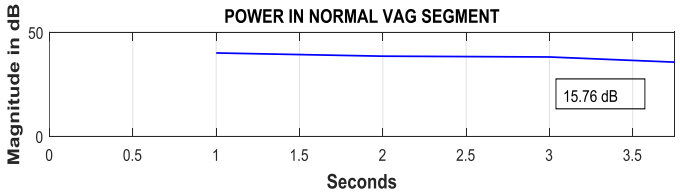


Fig.6(a). Averaged Power in Normal VAG signal

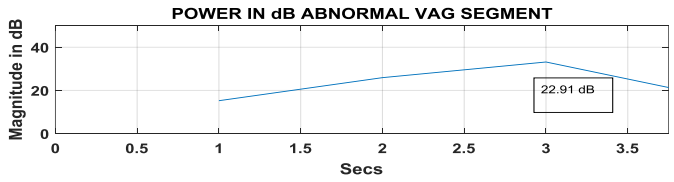


Fig.6(b). Averaged Power in Abnormal VAG signal

Considering the fact that automated assessment of diagnostic method to implementation is required. Following features by statistical approach: Variances, root mean square, inter quartile range features are identified. In order to justify non stationary and nonlinear dynamics nature of VAG, Hurst Exponent (HE), Fractal

Dimension (FD) and detrended fluctuation analysis (DFA) are also selected as features in feature set.

The algorithm analyses consecutive VAG signals of data with 50 percent overlap. The power of the signal segment is computed using spectral method, Convention Fourier domain using given set of equations,

$$X_{avg}^{(i)}(f)=\frac{1}{L}\left|\sum_{n=0}^{L-1}w[n]x_i[n]e^{-j2\pi f_n}\right|^2 \quad (1)$$

where,

$$P_M(f)=\frac{1}{K}\sum_{i=1}^{K}X_{avg}^{(i)}(f)$$

Finally, spectral power is computed using Eq.(2).

$$P_{M(VAG_{band})}(f)=\frac{1}{f_2-f_1}\sum_{f=f_1=10}^{f_2=1000}P_M(f) \quad (2)$$

Calculated values VAG Band (10 Hz-1000 Hz) is depicted in the Table.2, first column as dB. Since calculated value is average power of signal in dB.

Statistical methods provide information on the amplitude variation of VAG signal. Statistical parameters used are Variance (VAR), Root Mean Square (RMS), Standard Deviation (SD), Measure of Spread in terms of Inter Quartile Range (IQR), for understanding normal and pathological differences. The mean, standard deviation, RMS, MOS and IQR have the same units as the VAG signal amplitude, which is in volts whereas a unit of variance is the square of the volts.

The variance is the mean of the squared differences between individual data points and the mean of the array. Variance is calculated by using the Eq.(3)

$$v=\sigma^2=\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2 \quad (3)$$

where, $\bar{x}$ is the mean value of the signal and $x_i$ is the individual data points.

The standard deviation is the square root of the variance. The Root Mean Square (RMS), is a statistical measure of the magnitude of a varying quantity, RMS is calculated by Eq.(4).

$$\bar{x}_{rms}=\sqrt{\frac{x_1^2+x_2^2+...+x_N^2}{N}}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \quad (4)$$

The quartiles are computed by breaking data set into quarters. The measures available in quartiles are first ($Q_1$), second ($Q_2$) and third quartiles ($Q_3$). A common measure of depicting a quartile is an inter quarter range ($Q_3$-$Q_1$). Hence for a signal, the inter quartile range ($IQR$) is

$$IQR=Q_3-Q_1 \quad (5)$$

Chaotic behavior is a feature of nonlinear measures. A variety of chaotic and fractal measures have been developed to quantify changes in the VAG signal dynamics, it is required to find nonlinear parameters during screening. HE computation for computed here to know trend analysis, but as expected the results are showing small changes might be the HE value ranges 0 to 1. The DFA is a measure to find a long range correlation in non-stationary signals to be analyzed with '$N$' samples. DFA produces a fluctuation function of logarithm scale '$n$', integrated time series divided boxes of lengths. The FD is computed using 50% data overlapped and averaging is given by Eq.(6),

$$FD=\frac{\log_{10}(n)}{\log_{10}\left(\frac{d}{L}\right)+\log_{10}(n)} \quad (5)$$

Features required for automated detection and assessment of condition, the work is kept as a part for future development.

## 4. RESULTS

The features in Table.2 shows the distribution of spectral value Welch overlapped segmented Averaging (WOSA) in decibels (dB), column 2, 3, 4 and 5 are the statistical features such as variance (VAR), root mean square (RMS), inter quartile range (IQR). Column 5, 6 and 7 are subsequently nonlinear feature values Hurst's Exponent (HE), fractal dimension (FD) and detrended function analysis (DFA) computed for 24 normal segments.

The method is applied to pathological signals and computed feature values for the feature set as earlier discussed and the for the same, Table.3 is presented below.

Table.2. Results for normal VAG signals obtained from the method and showing the feature values

| Subject | Normal | | | | | | |
|---|---|---|---|---|---|---|---|
| | dB | VAR | RMS | IQR | HE | FD | DFA |
| 1 | -8.39 | 482.47 | 21.96 | 27.53 | 0.94 | 0.97 | 15.73 |
| 2 | -7.71 | 100.41 | 10.02 | 14.14 | 0.92 | 0.91 | 12.79 |
| 3 | -10.47 | 116.39 | 10.79 | 11.88 | 0.80 | 0.91 | 7.30 |
| 4 | -14.65 | 39.55 | 6.29 | 5.81 | 0.83 | 0.86 | 7.37 |
| 5 | -19.47 | 18.16 | 4.26 | 5.07 | 0.90 | 0.86 | 21.01 |
| 6 | -11.63 | 89.84 | 9.48 | 8.08 | 0.79 | 0.91 | 5.99 |
| 7 | -14.35 | 41.99 | 6.48 | 10.49 | 0.96 | 0.90 | 9.55 |
| 8 | -19.18 | 37.84 | 6.15 | 4.52 | 0.79 | 0.88 | 6.33 |
| 9 | -10.71 | 66.15 | 8.13 | 10.75 | 0.86 | 0.91 | 10.77 |
| 10 | -13.61 | 55.67 | 7.46 | 10.41 | 0.95 | 0.90 | 6.91 |
| 11 | -12.87 | 101.14 | 10.06 | 12.68 | 0.97 | 0.91 | 8.90 |
| 12 | -11.49 | 94.79 | 9.74 | 14.55 | 0.95 | 0.91 | 19.60 |
| 13 | -13.37 | 20.86 | 4.57 | 5.64 | 0.70 | 0.91 | 11.30 |
| 14 | -16.50 | 12.14 | 3.48 | 4.35 | 0.83 | 0.87 | 24.49 |
| 15 | -11.40 | 75.36 | 8.68 | 10.22 | 0.58 | 0.88 | 13.49 |
| 16 | -16.36 | 34.25 | 5.85 | 6.44 | 0.78 | 0.87 | 10.95 |
| 17 | -15.73 | 12.30 | 3.51 | 4.55 | 0.79 | 0.90 | 5.97 |
| 18 | -16.86 | 13.99 | 3.74 | 4.98 | 0.93 | 0.87 | 5.29 |
| 19 | -15.85 | 54.35 | 7.37 | 9.60 | 0.86 | 0.87 | 3.70 |
| 20 | -16.01 | 25.79 | 5.08 | 6.19 | 0.80 | 0.87 | 6.27 |
| 21 | -18.73 | 15.82 | 3.98 | 5.41 | 0.89 | 0.86 | 9.00 |
| 22 | -18.74 | 14.38 | 3.79 | 4.93 | 0.88 | 0.86 | 4.83 |
| 23 | -19.63 | 9.23 | 3.04 | 3.94 | 0.96 | 0.86 | 15.82 |
| 24 | -15.59 | 20.86 | 4.57 | 5.64 | 0.70 | 0.91 | 4.91 |

Table.3. Results for normal VAG signals obtained from the method and showing the feature values

| Subject | Abnormal | | | | | | |
|---|---|---|---|---|---|---|---|
| | dB | VAR | RMS | IQR | HE | FD | DFA |
| 1 | -4.27 | 693.61 | 26.33 | 47.39 | 1.00 | 0.90 | 9.50 |
| 2 | -5.17 | 264.53 | 16.26 | 19.63 | 0.86 | 0.92 | 14.46 |
| 3 | -7.60 | 65.87 | 8.12 | 10.45 | 0.84 | 0.92 | 12.13 |
| 4 | -6.10 | 546.33 | 22.54 | 35.54 | 0.92 | 0.92 | 18.86 |
| 5 | -4.43 | 556.25 | 23.58 | 34.36 | 0.99 | 0.90 | 9.72 |
| 6 | -4.81 | 162.86 | 12.76 | 16.51 | 0.87 | 0.93 | 13.58 |
| 7 | 1.75 | 292.38 | 17.10 | 16.32 | 0.86 | 0.96 | 34.78 |
| 8 | 3.62 | 383.51 | 19.58 | 17.75 | 0.92 | 0.96 | 39.27 |
| 9 | -5.99 | 657.03 | 25.63 | 18.98 | 0.82 | 0.97 | 18.78 |
| 10 | 3.26 | 788.77 | 28.08 | 16.11 | 0.75 | 0.96 | 31.74 |
| 11 | -5.55 | 264.53 | 16.26 | 19.63 | 0.86 | 0.92 | 14.46 |
| 12 | -5.12 | 146.57 | 12.11 | 15.85 | 0.86 | 0.94 | 19.40 |
| 13 | -2.99 | 695.48 | 26.37 | 34.26 | 0.90 | 0.93 | 28.28 |
| 14 | -5.74 | 642.78 | 25.35 | 14.98 | 0.77 | 0.96 | 50.48 |
| 15 | -6.54 | 733.78 | 27.09 | 29.35 | 0.87 | 0.94 | 30.38 |
| 16 | -1.05 | 661.56 | 25.72 | 24.89 | 0.71 | 1.07 | 51.26 |
| 17 | -9.24 | 273.73 | 16.54 | 20.61 | 0.81 | 0.92 | 16.14 |
| 18 | -5.17 | 846.32 | 29.09 | 25.58 | 0.72 | 1.07 | 34.02 |
| 19 | -7.47 | 136.67 | 11.69 | 16.00 | 0.86 | 0.90 | 10.43 |
| 20 | -3.86 | 233.64 | 15.28 | 14.38 | 0.78 | 0.91 | 13.23 |
| 21 | -7.40 | 489.05 | 22.11 | 19.31 | 0.81 | 0.90 | 8.53 |
| 22 | -5.14 | 65.75 | 8.11 | 7.24 | 0.77 | 0.87 | 3.97 |
| 23 | -5.64 | 72.0148 | 8.4851 | 3.638 | 0.55 | 0.8951 | 15.21 |
| 24 | -5.90 | 695.93 | 26.38 | 19.76 | 0.82 | 0.97 | 15.21 |

## 5. DISCUSSION

The features corresponding to of 24 normal VAG and 24 abnormal VAG signals, for are computed for Dataset 2. The Table.4 show the mean of the feature values computed for the aforesaid dataset. From the mean, variance and standard deviation calculation, it can be clearly seen that a difference is there in all parameters for normal and diseased conditions.

It is also inferred from the Table.4 that value of power for normal signals are less and that can discriminate pathological condition of knee sound signals with difference of about 10 dB. Similarly other features VAR, RMS, IQR, FD and DFA feature clearly distinguishing the conditions. HE, a nonlinear parameter shows slightly higher values for normal and bit less for abnormal conditions. These features are to be used further for classification, training and testing using neural network tools.

The VAR value for normal signal is obtained as (mean) 69.26 and for the abnormal to be as 436.41. There are significant and noticeable changes. The other parameters for strongly justify the feature set selection are suitable for further to proceed automated classification. Hence the features are highly distinguishable and predictable.

Table.4. Feature mean values for the 24 normal and 24 abnormal recordings

| Performance Metrics | Normal | | | | | | |
|---|---|---|---|---|---|---|---|
| | dB | VAR | RMS | IQR | HE | FD | DFA |
| Mean | -14.28 | 69.26 | 7.31 | 9.01 | 0.85 | 0.89 | 10.34 |
| Variance | 11.7 | 9647.07 | 16.53 | 28.13 | 0.01 | 0.00 | 31.01 |
| Standard deviation | 3.42 | 98.22 | 4.07 | 5.3 | 0.09 | 0.03 | 5.57 |
| | Abnormal | | | | | | |
| | dB | VAR | RMS | IQR | HE | FD | DFA |
| Mean | -4.32 | 436.41 | 19.8 | 21.6 | 0.84 | 0.94 | 21.97 |
| Variance | 11.51 | 64696.7 | 44.38 | 89.51 | 0.01 | 0.00 | 183.14 |
| Standard deviation | 3.39 | 254.36 | 6.66 | 9.46 | 0.08 | 0.05 | 13.53 |

The testing is carried out with 7 features for 48 subjects' data of 2 classes namely, normal and abnormal conditions. Fig.7 a) shows the experimental simulated network proposed.

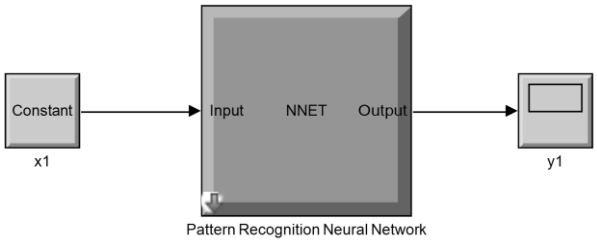


Fig.7(a). Proposed experimental network

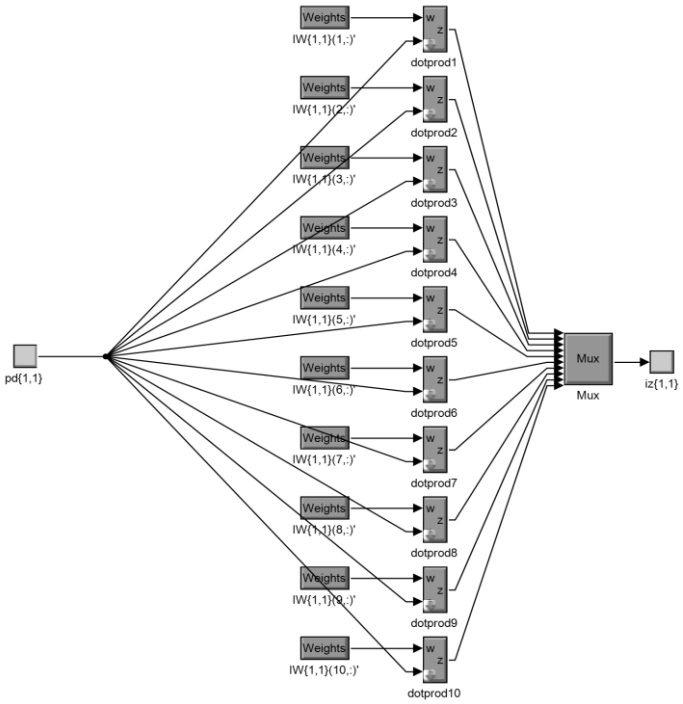


Fig.7(b). Proposed experimental networks

The present system neural network back propagation neural network (BPN) has been used. The back propagation contains three layers, input layer, hidden layer and output layer. It is a multilayered forward network using gradient based delta learning rule, generally known as back propagation rule or delta rule. BPN

algorithm consists of three main parts i) forward, ii) backward and iii) adjusts weighted value. The network is trained by supervised learning method. The ANN classifier is trained with Levenberg-Marquardt back propagation method. The number of inputs to the ANN is the 7 features computed and hence the input layer of the network, by default consists of 7 neurons. Only one hidden layer has been used. To calculate the number of hidden nodes, the general rule (the number of inputs + outputs) x 2/3 is used where number of inputs is 12 and outputs are1.Hence the network is designed to have 10 hidden layer neurons. Three output neurons are selected to indicate healthy ad diseased. The architecture of BPN is as shown in Fig.7.b) hardware simulated for the network deployment. Subsequently the analysis result presented here showing result Table.4.

Table.5. Comprehensive accuracy measures for the 24 normal and 24 abnormal recordings

| Measures | Value |
|---|---|
| TN | 24 |
| TP | 23 |
| FP | 0 |
| FN | 1 |
| Sensitivity | 95.80 % |
| Specificity | 100 % |
| Positive Predictive value | 100 % |
| Negative Predictive value | 96.00 % |
| Accuracy | 97.90 % |

## 6. CONCLUSION

This work has design and development of detection algorithm for knee joint assessment. In the development of detection algorithm; the changes in spectral power distribution during knee movements, considered as one of the feature (spectral domain) for detection. And remaining features from (time domain) the concept of statistical, nonlinear approaches. This method helps in development of automated detection. The proposed method is tested on 48 signals from the dataset recordings from Dataset. The Table.5 shows the comprehensive accuracy measures results. The overall accuracy of detection is 97.90 %.

In future, huge number of samples will be taken and deep learning classifier will be used to enhance the accuracy of the result.

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