Osteoarthritis Detection System using Optimal Dynamic Feature Configuration

Gan Hong Seng, Tan Tian Swee

Abstract**—**Cepstral analysis has been invariably applied in processing various signals in which include vibroarthrography (VAG). The cepstral analysis, however, requires substantial efforts to optimize its performance on VAG signal before real application for osteoarthritis detection is possible. In this paper, therefore, we attempt to analyze the VAG signals by implementing delta and energy features. The analysis involves 30 volunteers and 900 acquired VAG signals. Our study shows that delta and energy features are capable to signalize osteoarthritis to a certain extent with superior computational feasibility. In conclusion, this paper explores the applicability of energy property in analyzing the VAG signal for future VAG study. Furthermore, via this paper, we intent to draw attention of future research, particularly on the correlation among various clinical parameters, pathologic VAG signals and muscle contrary interference (MCI) effect.

Keywords**—**Delta, Energy, Signal Processing, Vibroarthrography

I. Introduction

The patellofemoral joint vibration signal generated by leg movement is conventionally termed as vibroarthrography (VAG) analysis [1, 2]. Early back in 17th century, Robert Hooke had recognized VAG analysis as a potential non-invasive alternative for detecting knee joint disease [4-7]. At the early stage of the scientific experiments on VAG signals, Steindler [8] attempted the utilization of cardiophone, oscilloscope and recorder to trace the signals emitted from knee joint movement. He was reported to be the first to record the knee angle and to enhance the VAG signals quality using filter. Chu et al. [9], in their evaluation of cartilage damage, observed that the energy parameter of the VAG signal correlates with the degeneration level of the knee joint in 1978.

VAG signals exhibit non-stationary nature, which is mainly attributed to the relationship between the effective joint surface contact area and moving angular position: During the articulation of the joint, friction between the bone surfaces beneath patella emits multiple vibrations; The friction releases multiple frequency vibrations that propagate through different medium of soft tissues and skin layers, producing multiple energy components at different angular positions. In previous studies, researches have reported sounds such as click, pop, grinding, and scraping being heard during the clinical auscultation. The findings reflect the temporal similarity between VAG signals with human speech signals [2]. These sounds have served as sound parameters in their experiments [5, 6, 10].

A. Related Work

Substantial amount of studies have been conducted to enhance the reliability of VAG signals to detect knee joint disorder. Tavathia et al. [5] proposed the application of linear prediction (LP) modelling in segmenting and extracting parameters from the VAG signals. In his study, feature vectors were derived by computing the LP model parameters using Levinson’s algorithm, extracting the dominant pole from the LP transfer function and calculating the spectral power ratio. The study concluded that the modelling technique has successfully extracted feature vectors from the signal but was limited by difficulty to define an adaptive segment boundary.

Zahra et al.[6] reported the use of Recursive Least Squares (RLS) modelling technique to adaptively segment the data samples into fewer model parameters and compute their means and variances of means (VM). Every VAG signal segment was modelled by forward backward linear prediction (FBLP) and feature vectors such as model coefficients and dominant poles were extracted using double precision arithmetic. Classifications based on two set of features: 40 model coefficients, VM and clinical parameters; and 10 dominant poles, VM and clinical parameters were carried out.

Krishnan et al. (who implemented Recursive Least Squares lattice (RLSL) for adaptive segmentation with a fixed threshold value of 0.9985) further improve the analysis method [11]: They implemented Burg Lattice method in Auto Regressive modelling (AR) of VAG signals. The extracted dominant poles represented the dominant frequencies of the system by taking account of clinical parameters. Krishnan’s methodology applied leaves one out (LOO) method to classify the AR coefficients along with the clinical parameters such as sound heard, age in years, gender and level of activity. The result achieves an accuracy of 68.9%.

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Momentarily, Rangayyan et al. [10] conducted the performance evaluation of various coefficients in representing the VAG signals. In the study, they extracted 3 types of features from adaptively segmented VAG signals: dominant poles, auto regression parameters and cepstral coefficients intending to enhance the comprehensiveness of the study. They included various clinical features in the study such as sound heard during auscultation, subjects' age and level of activities. Subsequently, these features were classified along with the parametric coefficients by using logistic regression method and LOO method. The finding suggested that cepstral coefficient emerged to be the best representation of the VAG signals among these 3 parameters.

In 2000, Krishnan et al. [2] proposed to decompose the VAG signal by applying Matching Pursuit (MP) algorithm into adaptive Time Frequency Distribution (TFD). After that, they extracted energy, energy spread; frequency and frequency spread are from the TFD. Statistical pattern classification system based on stepwise logistic regression analysis was applied to classify the signals without considering the joint angle and clinical information of the experiment subjects. This produced screening accuracy of 68.9% using 90 VAG signals.

Umapathy et al. [4] has suggested a novel VAG signals by decomposing the signals into highly discriminatory time frequency (TF) subspaces, followed by classification using Local Discriminant Bases (LDB) algorithm. The performance evaluation of the novel combination of wavelet packet decomposition and a modified LDB algorithm VAG signals analysis are conducted by introducing 3 dissimilarity criteria into the study. First dissimilarity criteria measured the difference in the normalised energy between corresponding nodes of training signals from different classes; second dissimilarity criteria represented the correlation value between the basis vector coefficients at the corresponding nodes; third dissimilarity criteria measured the randomness of the basis vector coefficients.

Keo et al. [7] has attempted the segmentation and normalisation of the VAG signals using Dynamic Time Warping (DTW). The study then converted the VAG signals into time frequency distribution (TFD) using Wigner Ville Distribution (WVD), reduced the noise using Singular Value Decomposition (SVD) and extracted time frequency features such as energy, energy spread, frequency and frequency spread from VAG signals. The study classified the signals using back propagation neural network (BPNN).

Rangayyan et al. [12] has conducted study on the possibility of using statistical parameters of VAG signals such as form factors for certain duration of the signals, skewness, kurtosis and, entropy to investigate the nature of the VAG signals. The study implemented the Fisher linear discriminant analysis (FLDA) to identify the pattern of the signals, where the best discriminant result was used to derive a receiver operating characteristics (ROC) curve for calculating the associated area under the curve using ROCKIT. The method was able to produce screening efficiency of up to 0.82 in terms of the area under the receiver operating characteristics curve.

In another work, Rangayyan et al. [1] has studied the parameters related to the variability of the VAG signals. The proposed features include an adaptive turn count and the variance of the mean squared valued for extension, flexion and full swing cycle of the leg in classifying the abnormal signals from the normal ones.by using similar classification procedure, the experiment has generated screening efficiency of up to 0.8570 in terms of the area under the receiver operating characteristics curve.

In latter attempt, Rangayyan et al. [13] has introduced a novel statistical modelling method to analyse the VAG signals statistical characteristics by studying their probability density functions (PDFs). Parzen windows were applied to derive the PDF models and Kullback-Leibler distances between the signals' PDF models were interpolated. An overall accuracy of 77.53%, sensitivity of 71.05%, and specificity of 82.35% were achieved in the PDF analysis.

In advance of the Parzen windows study, Rangayyan et al. [14] has suggested higher discriminant features could be available at the extension part of the VAG signals. Therefore, a novel fractal analysis to examine the temporal and spectral variability of the VAG signals. The fractal dimension features of the VAG signals based on certain normalised duration of the signal have been extracted through the Power spectrum analysis of VAG signals and classified by using LOO method and FLDA. Rangayyan et al. [14] concentrated on the classification of the screening system, thus, did not consider any clinical parameters in the study.

B. *Outline of the System*

The structure of this paper is organised as follow: section 2 will describe the VAG data acquisition procedure and VAG signal processing. In section 3, we will quantify the results and discuss the findings in section 4. We will present the conclusion and recommendation on future research. Fig. 1 illustrates the experimental procedures of this experiment.

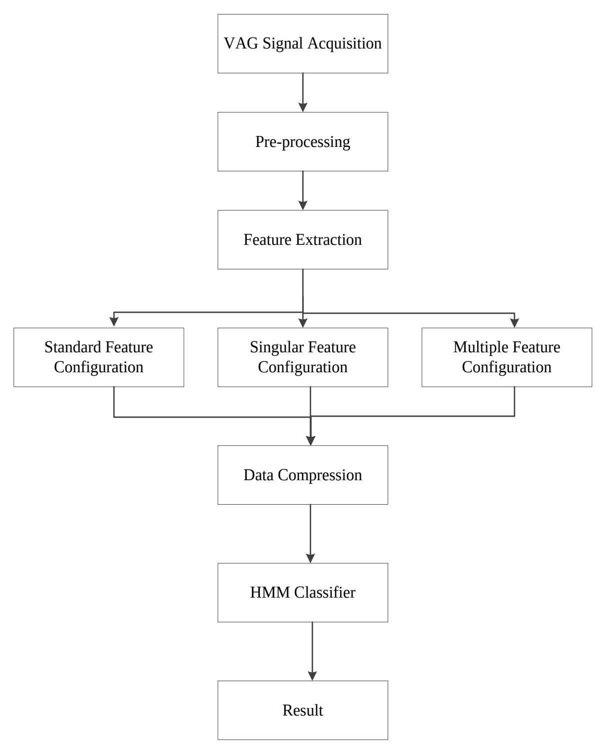

Fig. 1: Process flow of evaluating the performances of delta and energy features through different configurations of features

II. Development of the System

In this section, we will discuss the VAG signal acquisition, VAG signal pre-processing, feature extraction and classification process. In VAG signal acquisition, we have recognised the importance of several pre-recording elements such as number of subjects, auscultation location, knee angle, recording posture, recording duration and signal digitization. The details of aforementioned elements will be described in section 2.1.

In our study, 12 cepstral coefficients are extracted through the computation of standard LPCC and MFCC to be set as the referral to the following experiment results. The experiment is reiterated by adding delta (D) feature and energy (E) measure into the feature extraction process to further evaluate their effect on VAG signal cepstral coefficient analysis. We have proposed five configurations of delta feature and energy measure: delta (D), delta, delta-delta (D, DD), energy (E), delta, energy, delta-energy (D, E, DE) and delta, delta-delta, energy, delta-energy, delta-delta-energy (D, DD, E, DE, DDE).

In an initial attempt to establish a robust knee joint signal cepstral analysis system, our study has provided a comprehensive VAG signals cepstral analysis study by conducting analysis in intra-subject and inter-subject analyses using HMM classifier. The recognition rates of all six parameters configurations are gauged by using statistical measures and serve as reference to the future development of a VAG signals analysis system.

A. *VAG Data Acquisition*

In this work, VAG signals were derived from 30 normal subjects. Prior to the initiation of the recording process, participants were required to sit straight in relax mode and a stethoscope with electret microphone was attached to the medial condyle of patella. A full swing cycle that covered a 90 degree full flexion and a 90 degree full extension within a four second recording period was performed. All VAG signals were digitised at a sampling rate of 8 KHz. Fig. 2 shows a normal VAG signal sample acquired from a normal subject.

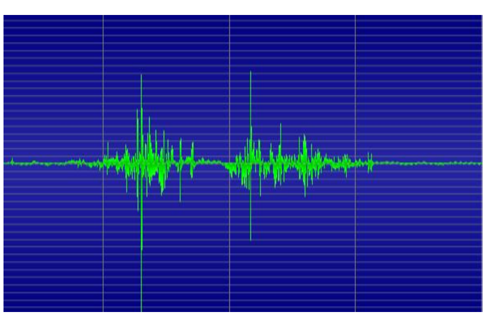

Fig. 2: Sample of VAG signal

B. *VAG Signal Pre-processing*

The high frequency bands of VAG signals are always weaker than that in lower frequency bands [10]. Therefore, the pre-emphasis filtering process will flatten the frames to boost the signal to noise ratio (SNR) of the VAG signals and reduce effect of attenuation distortion. In this work, we have selected a pre-emphasis filter coefficient, $\alpha = 0.95$. (1) illustrates the mathematical expression for our pre-emphasis filter.

$$H(z) = 1 - 0.95z^{-1} \tag{1}$$

We face the problem of leaking during the flame-blocking process of non-stationary VAG signals. In order to minimise the spectral leakage and artefacts, VAG frames will pass through Hamming window [15].

Hamming window is a versatile windowing technique capable of retaining the good frequency resolution of the signals. In present work, each Hamming window has a size of 20 ms and there are 166 frames in each signal. Every segment has an overlapping of 33.33% among each other to avoid discontinuities on both side lobes of the window. The stationary frames will undergo Discrete Fourier Transform (DFT) where the frames are transformed from time domain to frequency domain [16]. The mathematical expression of Hamming window is illustrated in (2).

$$W(n) = 0.54 - 0.46\cos(2\pi n / N - 1) \tag{2}$$

III. Feature Extraction

Desired information is extracted from the VAG signals by using MFCC and LPCC in this experiment. Both MFCC and LPCC extract important spectral information from the short time windowed VAG segments [18, 33] and each signal will be represented by 12 cepstrum coefficient values. Besides, Delta (D) and Energy (E) coefficients are introduced into the feature extracting process to analyze the nature of VAG signals through quantitative results.

A. *Mel-frequency Cepstral Coefficient (MFCC)*

MFCC was developed based on the concept that human ear focuses non-uniformly in the spectral envelop [28]. Since its inception, MFCC proves to be widely popular in the human speech analysis given its ability to extract phonetically important information of the signals by focusing in the lower range of the Mel frequencies.

The process of MFCC application starts by filtering the VAG signal with pre-emphasis filter and transforms the signal into frequency domain using DFT in the pre-processing stage. Thereafter, the DFT is transformed into Mel-frequency scale by using a set of triangular bandpass filters. The procedure of executing MFCC is illustrated in Fig. 3. These filters act linearly at the range between 0 to 1000 Hz but increases logarithmically for frequency above 1000 Hz [17, 18]. The mapping of linear frequency to Mel frequency or Mel-frequency wrapping is shown in (3) and its critical bandwidth function could be calculated by applying (4). The application of MFCC in VAG signals is illustrated in Fig. 3.

$$Mel(f) = 2595\log_{10}\left[1+\left(f/700\right)\right] \quad (3)$$

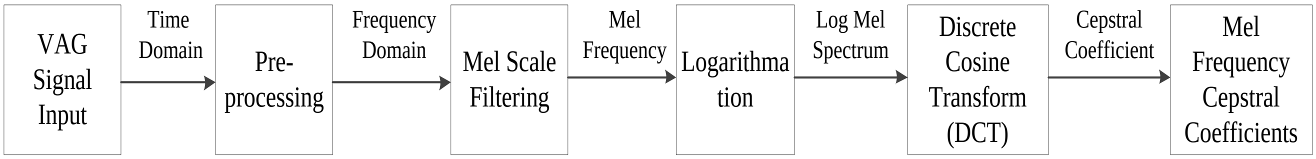

Fig. 3: MFCC computational procedures for VAG signals where the VAG signals are required to be transformed into Mel frequency to extract the cepstral features.

$$BW_{critical} = 25 + 75\left[1 + 1.4\left(f/1000\right)^2\right]^{0.69} \quad (4)$$

This representation allocates more weight to the log DFT output amplitudes from lower frequency range. The Mel parameters are transformed into cepstral coefficients in time domain by using Discrete Cosine Transform (DCT). The computational of the DCT is shown in (5).

$$MFCC_i = \sqrt{\left(2/N\right)}\sum_{j=1}^{N} m_j \cos\left[\left(\pi i/N\right)(j-0.5)\right] \quad (5)$$

A. *Linear Predictive Cepstral Coefficient (LPCC)*

LPCC derives from the Linear Predictive Coefficients (LPC) [19, 31] and represents the best linear predictive feature among LP derivatives. LPC extracts characteristic of the vocal tract by using pre-emphasis filter [23, 32]. LPC can be computed through the transfer function of the all pole model filtering in *z* transform can be represented by *H(z)*. In this experiment, we set the predictor coefficient, $\alpha = 0.95$ and number of modeling order, *p* at 12 in order to minimize the mean squared error of the VAG signal.

The all pole model transfer in time domain could be illustrated through Fig. 4. The z-transform of the all pole model is illustrated in (6).

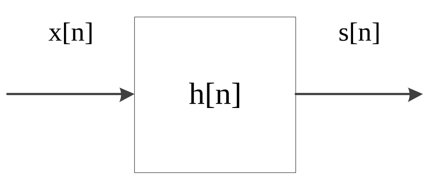

Fig. 4: An example of the all-pole model

Prediction coefficient is an important element in LPCC because these coefficients represent the VAG formants. We could estimate these coefficients and their gain factor minimizing the mean-square error (MSE) between the predicted VAG signal and the actual VAG signal. The transfer function of the all pole model filtering in *z*-transform can be represented by *H(z)* and the function's mathematical expression is shown in (6) and (7) [20].

$$H(z) = S(z)/X(z) \quad (6)$$

$$H(z) = G/[1 - \sum_{K=1}^{p} \alpha_{K}^{p} z^{-k}] \quad (7)$$

The LPCC is the equivalents of to the smoothed envelop of the log spectrum of the speech in MFCC. However, LPCC decomposes the smoothed spectrum envelop to extract desired features while MFCC extracts desired features directly from the DFT power spectrum. LPCC computes the traditional LPC coefficients by recurring LPC parameter. LPCC is computed from LPC and is shown in (8) [20]

$$LPCC_i = \sum_{j=1}^{p}\left(K - i/i\right) LPCC_{i-j} LPC_j; i > p \quad (8)$$

B. *Delta and Energy parameters*

Although cepstral coefficient carries vital spectral information of VAG signals that plays significant role in classification system [10], variation occurs during VAG signal processing procedures. The feature vectors consisting of only MFCC and LPCC parameters appear to be able to provide smooth estimates of the local spectrum. But these features lack information regarding the speech signal dynamic evolution, which also carries other relevant information in VAG signal recognition. On the ground of the limitation posed by the standard MFCC and LPCC technique in analyzing the VAG signals, improvements in recognition performance can be obtained by taking into account the dynamic characteristics of the MFCC and LPCC features.

The simplest approach to obtain these dynamic features takes the basic difference of coefficients between consecutive frames. The resulting coefficients, known as linear delta parameters, reflect cepstral changes over time. By introducing the delta and energy parameters into the standard MFCC and LPCC parameters, the performance of the feature analysis are perceived to be able to improve significantly. The delta parameter can be derived by regression formula where the delta parameter d_i at time *t* can be computed in terms of corresponding static coefficients $c_{i-\theta}$ and $c_{i+\theta}$ [21]. (9) and (10) show the derivations of delta and delta-delta features.

$$d_i = \left(\sum_{\theta=1}^{\Theta} \theta (c_{i+\theta} - c_{i-\theta}) \Big/ 2\sum_{\theta=1}^{\Theta} \theta^2 \right) \quad (9)$$

$$dd_i = \left(\sum_{\theta=1}^{\Theta} \theta (\Delta c_{i+\theta} - \Delta c_{i-\theta}) \Big/ 2\sum_{\theta=1}^{\Theta} \theta^2 \right) \quad (10)$$

Energy measure is originally computed to distinguish between voiced sounds and unvoiced sound in speech signal processing due to its simple implementation and efficiency. There are three forms of energy parameters: logarithmic short term energy, squares short term energy and absolute short term energy. In this paper, we proposed the use of logarithmic short term energy parameter to enhance the performance of the cepstral analysis. The logarithmic short term energy is computed by summing the squared magnitudes of the VAG signal samples in each frame and performs logarithmic function. The logarithmic short term energy is computed as below:

$$E_{\log} = \log \sum_{n=1}^{N} \left| x^2[n] \right| \quad (11)$$

In our present work, we have introduced three types of feature configurations i.e. standard configuration, single feature configuration and multiple features configuration. The standard configuration consists of original cepstral coefficients, whereas the single feature configuration comprises of the adding delta or energy features into the standard configuration. The multiple features configuration is made up of standard configuration along with the delta and energy features arranged in different positions. Table 1 shows the categorization of feature configuration proposed in this paper and their parametric values.

Table 1: The LPCC and MFCC feature configuration categorisation and their parametric values according to types of features being implemented onto respective configuration.

Types of feature configuration	Number of parameter
Standard configuration	
LPCC	12
MFCC	12
Single feature configuration	
LPCC D	24
LPCC E	13
MFCC D	24
MFCC E	13
LPCC D, DD	36
MFCC D, DD	36
Multiple features configuration	
LPCC D, E, DE	26
LPCC D, DD, E, DE, DDE	39
MFCC D, E, DE	26
MFCC D, DD, E, DE, DDE	39

IV. VAG Classification System

Our prior study has been focusing on traditional cepstral analysis. In this paper, we would classify our VAG signals according to two evaluation elements. First, we would divide the classification into intra-subject and inter-subject analysis. Second, we would classify the VAG signals according to abovementioned dynamic feature configurations. A total of 30 VAG signals are included into this paper and we have continued to use HMM for the classification stage.

A. Data Feature Reduction

After the VAG signals undergo feature extraction, the amount of data are further reduced by encoding the signal data statistically into a set of k-dimensional of data vector or codeword, c_i where i = 1, 2, 3 … using iterative clustering algorithm. These set of data vectors are represented by a finite set of M symbols. The recursive training process produces a complete set of M codewords known as codebook.

During the encoding process, every newly encoded k-dimension vector X_i is compared to each of the M codewords in the codebook. The distortion $D(X_i, C_i)$ between the input data vector and the codeword is computed to find out the minimum distortion. The average quantization distortion is an important element which is used to match score during the identification process [22]. The average quantization distortion with N frames is defined as below:

$$D(X, C) = \left(1/N\right) \sum_{i=1}^{N} \min_{cj \in C} \left\| X_i - C_j \right\| \quad (12)$$

The primary computational burden during the encoding process is that of computing the distortion between the input vector and each of the M codewords. In this experiment, a codebook 64 bit per vector dimension is deemed to be appropriate.

B. Hidden Markov Model (HMM)

A HMM is a Markov chain where the output observation is a random variable depends on the output probabilistic function associated with each state [23]. Five essential elements that weighted in our HMM classifier is [24]:

*(1)*The number of hidden states in the model, *S*
(2)The number of distinct observation symbols, *K*
(3)The state transition probability matrix, A = $\{a(i|j)\}$ where $a(i|j)$ is the probability of taking a transition from state *i* to state *j*
(4)The set of state output probability distribution, B = $\{b_i(o_t)\}$ where the $\{b_i(o_t)\}$ is the probability of emitting O_t when the state i is entered

(5)The initial state distribution, $\pi = \{\pi_i\}$

Two important assumptions, i.e. first order process assumption and independent observation assumption have been applied in the HMM to reduce the number of parameter that need to be estimated as the model complexity without significantly affecting the VAG signal analysis performance.

The first order Markov assumption states that the state transition at time t depends only on the previous state at time $t-1$. (13) depicts the mathematical expression of state transition probability that is not time variant.

$$P(Q|\lambda) = P(q_1, q_2, ..., q_T|\lambda) = \pi_{q_1} a(q_2|q_1) a(q_3|q_2) ... a(q_T|q_{T-1}) \quad (13)$$

The output independence assumption states that the present observation depends only on the current state and neither chain evolution nor past observations influence if the last chain transition is specified. The mathematical expression of the second assumption is stated in (14).

$$P(O|Q,\lambda) = P(o_1, o_2, ..., o_T|q_1, q_2, ..., q_T, \lambda) = P(q_1|\lambda) \prod_{t=2}^{T} P(q_t|q_{t-1}, \lambda) \quad (14)$$

HMM is suitable for this study because of the non-stationary characteristic of VAG and the HMM capability in capturing the non-linear variability in auscultatory signals[25]. In this paper, we used the five states left to right Hidden Markov Model. The matrices of the model parameters, where t = 1, 2, 3… are given as below:

$$A = \begin{bmatrix} P(q_t|1) P(q_t|2) P(q_t|3) P(q_t|4) P(q_t|5) \\ P(q_t|1) P(q_t|2) P(q_t|3) P(q_t|4) P(q_t|5) \\ P(q_t|1) P(q_t|2) P(q_t|3) P(q_t|4) P(q_t|5) \\ P(q_t|1) P(q_t|2) P(q_t|3) P(q_t|4) P(q_t|5) \\ P(q_t|1) P(q_t|2) P(q_t|3) P(q_t|4) P(q_t|5) \end{bmatrix}$$

$$\pi = \begin{bmatrix} P(1) \\ P(2) \\ P(3) \\ P(4) \\ P(5) \end{bmatrix}$$

$$B = \begin{bmatrix} P(o_t|1) P(o_t|2) P(o_t|3) P(o_t|4) P(o_t|5) \\ P(o_t|1) P(o_t|2) P(o_t|3) P(o_t|4) P(o_t|5) \\ P(o_t|1) P(o_t|2) P(o_t|3) P(o_t|4) P(o_t|5) \end{bmatrix}$$

V. RESULT

In this section, two imperative evaluations based on VAG signals cepstral analysis have been examined and discussed. The first evaluation will assess the robustness of delta parameter and energy measure in VAG signal recognition; the second evaluation will investigate the variations among different types of parameter combinations and provide idea on the future research of VAG signal through cepstral approach.

The novel study on the delta and energy features in VAG signal cepstral analysis emphasizes on gauging the screening accuracies of standard, singular and multiple configurations in the cepstral analysis. Our objective in this paper is to enhance the performance of the VAG signals classification system using HMM. Hence, we do not consider the clinical parameters.

In the intra-subject analysis category, delta and energy features are imposing positive effect on VAG signal except LPCC D for the LPCC section. The MFCC section illustrated mixed results as the standard MFCC configuration showed slight superiority over MFCC D, MFCC D,DD and MFCC D,E,DE. By using *p*-value to illustrate the correlation between standard and featured configurations, the LPCC produced *p*-value of 0.3799 while the MFCC produced *p*-value of 0.6687. Both *p*-values are statistically insignificant; translate into the indifferences between the performances standard and experimental of LPCC and MFCC in small scale classification systems. The results are shown in Table 2.

In the inter-subject analysis, the featured configurations of LPCC and MFCC do not exhibit any significant improvement in recognition rates as standard LPCC and MFCC endure sharp fall in recognition rates in large scale database. LPCC E, LPCC D,E,DE, and LPCC D,DD,E,D,E,DDE outperform standard LPCC but the recognition rates remain highly unsatisfactory. In the MFCC section, four configurations of MFCC, with the exception of MFCC D, outperform standard MFCC but the recognition rates are even lower than LPCCs'. The standard and featured LPCC configurations gave *p*-value of 0.39 while the standard and featured MFCC configurations gave *p*-value of 0.1382. Both *p*-values are statistically insignificant from the perspective of statistical analysis. The results are shown in Table 3.

Our study separately investigates the exact effect of energy, delta and delta-delta features on VAG signals. Table 4 shows the result of the investigation. We could observe LPCC E and MFCC E outperforms LPCC D and MFCC D regardless of the database scale and types of feature extraction method being applied. Besides, all energy feature cepstral analysis regardless of feature extraction method, have outperformed their respective standard recognition rates while all delta feature cepstral analysis regardless of their feature extraction methods, have underperformed their respective standard recognition rates.

Table 2: Comparison between recognition rates of standard configuration with singular and multiple configuration in the intra-subject analysis category. *p*-value must be smaller than 0.05 in order to assume the parameter as statistically significant.

	Standard	**Singular**		**Multiple**			***p*- Value**
		D	E	D,DD	D,E,DE	D,DD,E,D,E,DDE	
LPCC Averaged Recognition Rate, %	90.17	89.5	90.50	90.50	90.67	90.83	0.3799
MFCC Averaged Recognition Rate, %	88.83	88.67	89.33	87.67	87.33	90	0.6687

Table 3: Comparison between recognition rates of standard configuration with singular and multiple configuration in the inter-subject analysis category. *p*-value must be smaller than 0.05 in order to assume the parameter as statistically significant.

	Standard	**Singular**		**Multiple**			***p* Value**
		D	E	D,DD	D,E,DE	D,DD,E,D,E,DDE	
LPCC Recognition Rate, %	60.33	58.33	64.17	60.17	61.83	61.83	0.3900
MFCC Recognition Rate, %	56.83	56.67	57.00	57.17	58.50	57.83	0.1382

Table 4: Quantitative analysis for single feature LPCC and MFCC configuration according to the class of database to compare the performances of delta and energy feature in LPCC and MFCC

Types of analysis	**Recognition rates**	**Standard**	**Singular**		**Multiple**
			D	E	D, DD
Intra-subject analysis	LPCC Averaged Recognition Rate, %	90.4	89.5	90.50	90.50
	MFCC Averaged Recognition Rate, %	88.83	88.67	89.33	87.67
Inter-subject analysis	LPCC Recognition Rate, %	60.33	58.33	64.17	60.17
	MFCC Recognition Rate, %	56.83	56.67	57.00	57.17

I. Discussion

In this study, we have observed the effect of singular and multiple feature configurations on the VAG signal. The addition of delta and energy features has brought several implications to our VAG signals screening system. The delta and energy features have increased the complexity of the system, but do not improve the robustness of the system and leads to the contrary to conventional concept that including the dynamic features into the signal analysis system will help in creating a robust signal recognition system [26].

On further investigation, we have discovered the importance of energy characteristic of the VAG signal over its time properties by analysing the singular feature configurations and the DD feature configuration. The imminent inclination of VAG signals toward the energy feature is observed in intra-subject and inter-subject analyses. This inclination could be viewed as a future indicator for VAG signal because the energy spectral could be highly discriminative information for accurate analysis.

We have interpreted the outcome of the second evaluation from another perspective where this outcome can be advantageous to the cepstral analysis of VAG signals in long term prospect because we can focus on modifying the conventional cepstral analysis for VAG signals rather than emphasizing on burdening the system by introducing more features. In the case of LPC, the complexity of the system depends on the p^{th} order of the LP modelling [27].

II. Conclusion

We have proposed the use of delta and energy parameters in an initial attempt to boost the VAG signals screening system. During the experiment, we have established better understanding of the nature of VAG signals by conducting quantitative analysis on the signals. Our study have concluded that the VAG signal screening system using cepstral analysis requires no additional feature since the statistical insignificant *p*-values produced by standard LPCC and MFCC and experimental LPCC and MFCC are indicating the relatively similar in performances of singular and multiple feature configurations. This evaluation gives rise to a new concept that advocates the use of standard feature extraction methods with adaptive modification for VAG signal representation. Furthermore, our study reveals the prominent energy feature in characterizing VAG signal. On the ground of this finding and current limitation of radiography technique such as X-ray in delineating cartilage tissue [29A3,30A4], we strongly recommend future exploration on the energy orientated nature of the VAG signals in which an optimal model serves great potential to drawbacks faced by image processing techniques [34A1, 35A2].

We attribute the main limitation of the study to the exclusion of abnormal VAG signal and clinical parameter in analyzing VAG signal. Furthermore, we have ignored the muscle contract interference (MCI) since the effect on VAG signal is minimal. Future researches should include abnormal VAG signal and focus on energy property of VAG signal if the intention is to increase the reliability of using cepstral coefficient in the VAG signal analysis.

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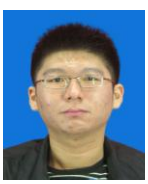

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