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Use of incremental decomposition and spectrogram in vibroacoustic signal analysis in knee joint disease examination

Abstract. *This paper presents two methods that enable indication of chosen dysfunction of knee joint: different stages of chondromalacia and osteoarthritis. The incremental decomposition of voltage in time and spectrogram were used. Both methods enable detection and identification of particular stages of knee joint dysfunction.*

Streszczenie. *W artykule zaprezentowano dwie metody umożliwiające wykrywanie wybranych dysfunkcji stawu kolanowego: różnych stadiów chondromalacji oraz choroby zwyrodniowej. Zastosowano metody badania rozkładów przyrostów przebiegów oraz spektrogram. Obydwie metody umożliwiają detekcję oraz identyfikację poszczególnych schorzeń.* ***Dwie metody umożliwiające wykrywanie wybranych dysfunkcji stawu kolanowego: różnych stadiów chondromalacji***

Keywords: knee joint dysfunction, signal processing, spectrogram, incremental decomposition.
Słowa kluczowe: dysfunkcje stawu kolanowego, przetwarzanie sygnałów, spektrogram, analiza przyrostowa.

Introduction

Joint dysfunctions are the most common disorders in human locomotor system. Complex biomechanical environment makes the knee joint particularly susceptible to such disorders [5]. Although X-ray has a number of advantages and is still a basic form of assessment of the articular system, this method presents some limitations that significantly reduce its clinical relevance [6]. On the other hand, access to more sensitive and specific imaging methods (e.g. MRI) is significantly limited due to high costs. In addition, it should be noted that these methods allow only for structure evaluation, without the assessment of the joint function [1].

Vibroarthrography (VAG) is an experimental method for assessing the function of articular structures. This method bases on recording mechanical vibrations generated by moving articular cartilaginous surfaces, which under physiological conditions reduce the coefficient of friction [2, 3]. However, in the course of various disorders within the articular system the cartilage structures are damaged or the changes in their biomechanical characteristics appear. This results in increased friction and increased vibrations corresponding to the degree of damage to the joint [2].

Because of its non-invasive character and relatively low cost, VAG method appears to be a promising diagnostic tool that can be used in clinical conditions. However, it is necessary to develop algorithms that classify individual disorders with respect to generally accepted diagnostic criteria. Therefore, the aim of this paper is to use the incremental decomposition and spectrograms in the analysis of vibroarthrography signals representing different levels of cartilaginous disorders within the knee joint.

Measurement methodology

The VAG signal was recorded using the 4513B-002 accelerometer sensor and the Brüel & Kjær Nexus 2692-C signal amplifier connected to an analogue-to-digital converter and a PC. The sensor was attached to the skin by the two-sided adhesive tape 1 cm above the apex of the patella. After the sensor was attached, the patient was instructed on the test that involved joint movement of 82 beats per minute in the metronome. The tests were held in a sitting position and consisted of repeated flexion and extension in the 90° -0° -90° range in the open kinematic chain. The test lasted 6 seconds, during which four full flexion/extension cycles were performed. The VAG signal was recorded in the frequency range of 0.7-1000 Hz at a sampling frequency of 10 kHz .

Incremental decomposition of voltage in time

The decomposition of voltage increments over time is derived from the author's algorithm created to reduce the number of calculations required to obtain the signal decomposition. This algorithm calculates how much the values of consecutive samples have changed, subtracting them from each other, and it creates a signal decomposition by increasing the number of occurrences of the increments in the resultant decomposition vector. Figure 1 shows the calculation algorithm for the described decomposition.

All calculations are done in a single loop. The variable *i* is the sample number, *d* is the temporary value of the calculated difference between samples, *s* is the input signal vector and *o* is the resultant vector of decomposition. Calculations begin with the reset of the variable *i,* whose value is then compared to the number of samples minus 1. If it is smaller, the calculations are continued. Then the variable *d* is calculated, which is the absolute value of the difference between successive samples of the input signal. After it has been calculated, the resultant decomposition vector is increased to the unit where the index of the variable is equal to *d*. The last step is to increase the value of the variable *i* and return to the conditional flow chart. The calculation ends when the value *i* reaches the number of samples.

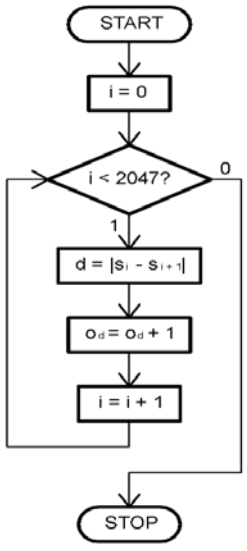

Fig. 1. Incremental decomposition algorithm [4].

The first advantage of calculating the decomposition of current increments over time is operating only on integers that are the simplest to be processed by microcontrollers. The second advantage involves the types of mathematical operations that are used when calculating individual decomposition. The algorithm uses subtraction and addition operations that are performed faster than multiplication and division. The above advantages make it possible to implement an algorithm for calculating the distribution of current increments over time on the simplest microcontrollers.

Spectrogram and time-frequency plane

The most popular tool used to determine the signal spectrum is Discrete Fourier Transform (DFT), and in particular its optimized algorithm - Fast Fourier Transform (FFT). Due to the requirement of stationary signal during the DFT window, Short-Time Fourier Transform (STFT) is used for non-stationary waveforms. Many applications use the DFT extension with a superimposed time window. Straight STFT is presented by dependence (1) [7]:

$$STFT(t, f) = \int s(\tau)\gamma^*(\tau - t)e^{-j2\pi f\tau} d\tau \quad (1)$$

where: $s(t)$ – signal in time domain, $\gamma(t)$ – analysis window.

The square of the STFT module is called SP spectra and is expressed by (2). This is the simplest example of the temporal representation of the signal energy in the time-frequency plane [8]:

$$SP(t, f) = |STFT(t, f)|^2 . \quad (2)$$

STFT and spectrogram are used for signal analysis in many areas of science and technology. This is especially the case in waveform analysis, which consists of periodically occurring signal components: electric waveforms [9], ECG waveforms or VAG signals [10].

The time-frequency analysis allows for obtaining a time-frequency plane where individual components can be identified and their occurrence, frequency and intensity times can be determined. The intensity of the individual components is proportional to the energy of the signal. It is also possible to determine the marginal conditions obtained by integrating the time-frequency plane over the frequency (time-marginal condition) and over time (frequency-marginal condition). The time-marginal condition represents the fluctuation of the signal energy over time, while the frequency-marginal condition presents the spectral content of the signal over the entire duration of the signal [8].

In addition, it is possible to determine the energy occurring at a specific time and frequency interval and to define a time profile for a particular frequency or frequency profile for a fixed time.

Results of use of incremental decomposition

For testing of incremental decomposition method was considered VAG signals for groups of 26 patients: control group patient (N), patients with chondromalacia stage I, II, III (ChI, ChII and ChIII), and with osteoarthritis (OA). VAG signals in every group were averaged.

Incremental decomposition very well presents sudden changes in signal, noise and interference. Consequently, it was used to process knee vibration measurements during the three subsequent stages of chondromalacia development and degenerative knee. Fig. 2 presents an incremental decomposition of healthy knee vibrations (N). Figs. 3, 4 and 5, respectively, show results of decompositions of knee vibrations of persons in three subsequent stages of chondromalacia development, and Figure 6, decomposition of degenerative knee vibrations (OA). Each decomposition was calculated on a signal containing 61440 samples. In addition, to improve the readability of the charts, averaging results were used in the area of 40 neighboring increments.

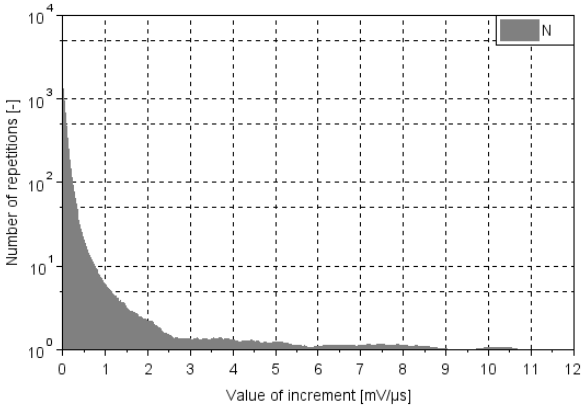

Fig.2. Incremental decomposition of VAG signal of healthy person.

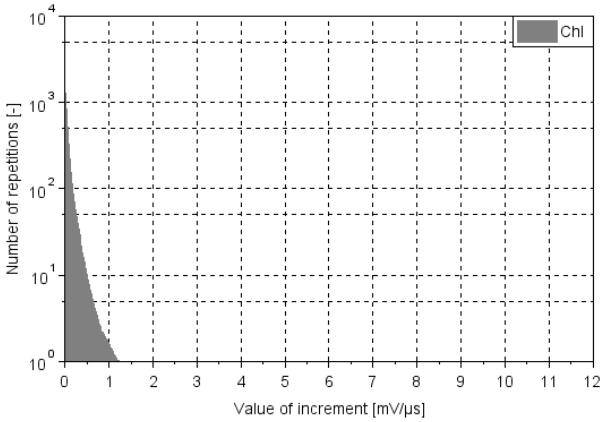

Fig. 3 VAG signal decomposition in stage I chondromalacia.

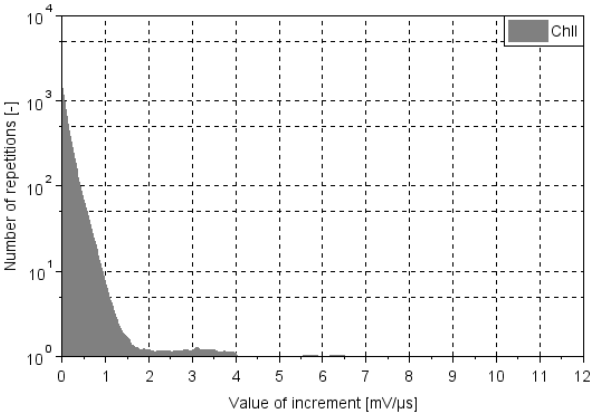

Fig. 4. VAG signal decomposition in stage II chondromalacia.

The incremental decomposition of VAG signal in the healthy person shows how the knee vibrations should look like as a reference point in diagnosing stages of the disease and degeneration. The decomposition in Figure 3 shows that during the first stage of chondromalacia. increments of more than 1.25 mV/μs do not occur as it was in the case of a healthy person. During the second stage of chondromalacia, the decomposition is shown in Fig. 4. vibrations of higher values begin to occur and terminate at 6.5 mV/μs and the graph starts to move towards higher

increases. The decomposition in Fig. 5 shows in the third stage of chondromalacia this trend continues and vibrations of values up to 8.5 mV/μs occur. VAG signal decomposition of the knee with degeneration shown in Figure 6 reveals a sharp decrease in the vibration of 0.5 mV/μs relative to the III chondromalacia stage and an increase in the number of increments of up to 5.5 mV/μs.

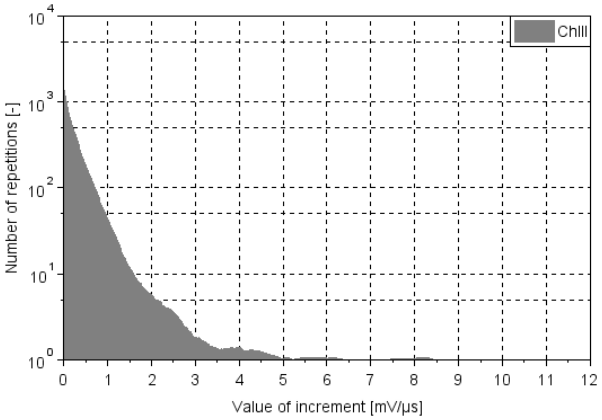

Fig. 5 VAG signal decomposition of person in stage III chondromalacia.

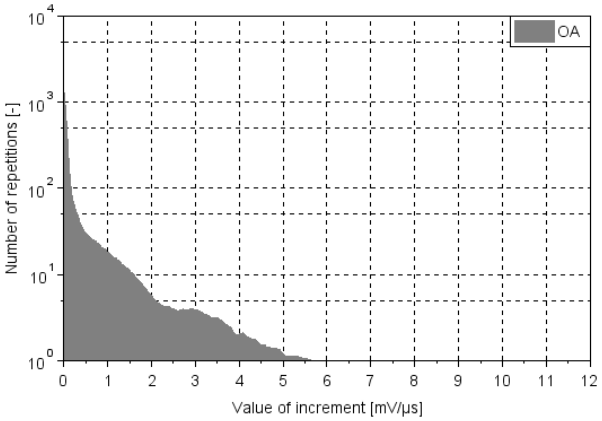

Fig. 6. VAG signal decomposition of the person with osteoarthritis.

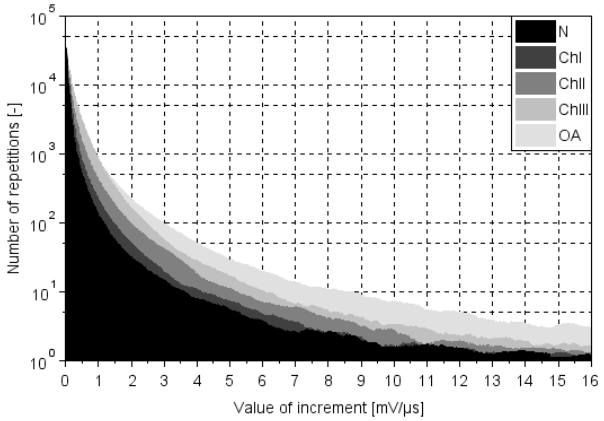

Fig. 7. The incremental decomposition of VAG signals of the healthy person (black), people with subsequent stages of chondromalacia (increasingly lighter gray) and degenerative knees (the lightest gray).

The tendency shown in Figures 3, 4, 5 and 6, involving shift of the decomposition towards higher increments is also present in the case of comparison of VAG signal decomposition of the healthy person and the person during the first stage of chondromalacia. It is presented in Figure 7.

Fig. 7 shows all of the above decompositions in one graph, but here 26 signals of 61140 samples for each case have been taken into account. For a healthy person the number of increments at 2 mV/μs was 41. As the subsequent stages of the disease develop, the number of repetitions of a given increase is 90 for the first stage, 178 for the second stage, 271 for the third stage, and 367 for degeneration.

Results of spectrograms

For investigating of spectrogram application in VAG processing, VAG signals for five groups of 20 patients was considered:

- control group patient (N),
- patients diagnosed with:
  - chondromalacia stage I (Ch I),
  - chondromalacia stage II (Ch II),
  - chondromalacia stage III (Ch III),
  - osteoarthritis (OA).

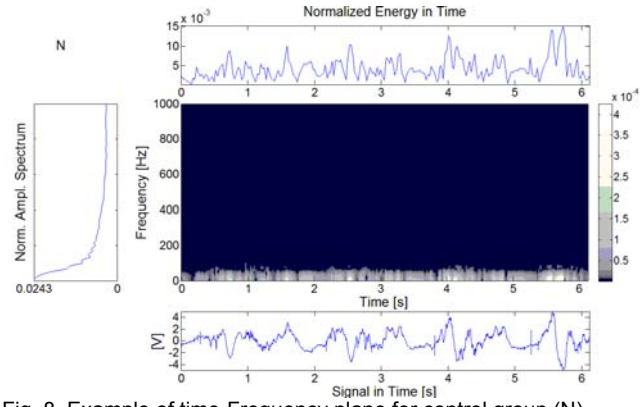

Fig. 8. Example of time-Frequency plane for control group (N).

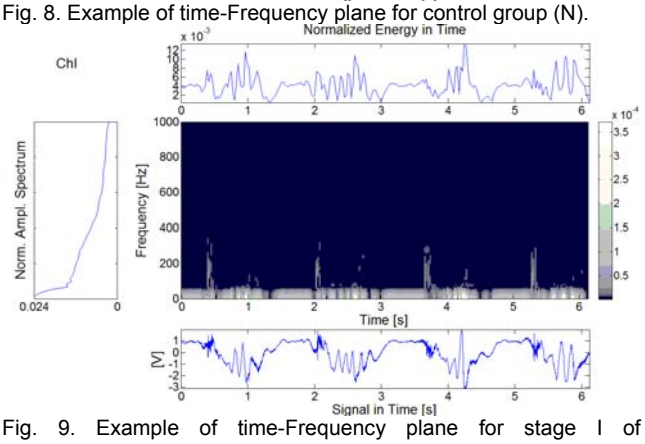

Fig. 9. Example of time-Frequency plane for stage I of chondromalacia group (Ch I).

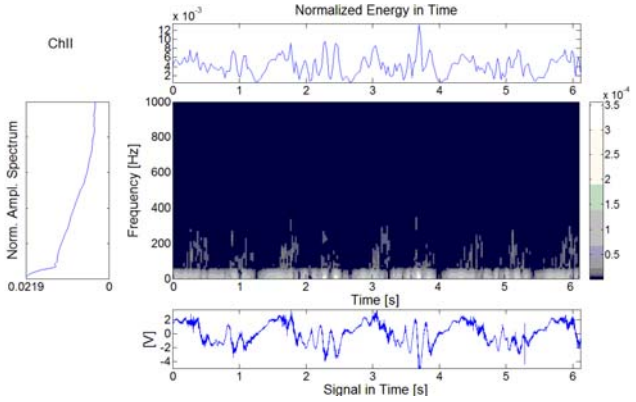

Fig. 10. Example of time-Frequency plane for stage II of chondromalacia group (Ch II).

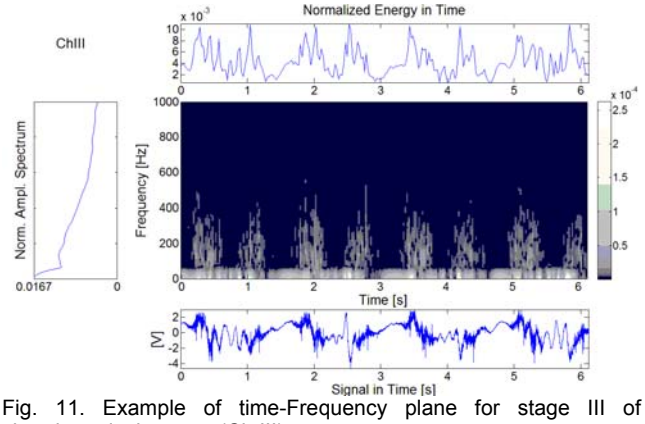

Fig. 11. Example of time-Frequency plane for stage III of chondromalacia group (Ch III).

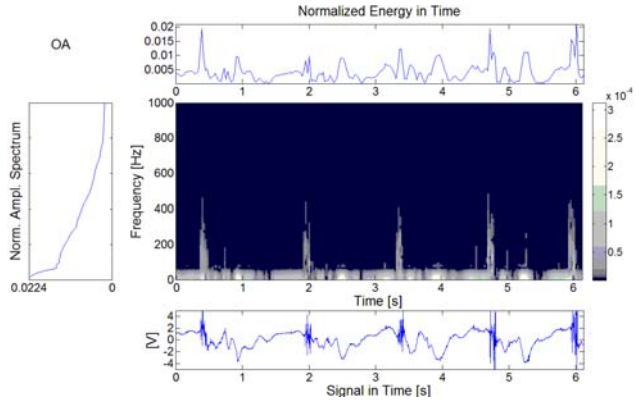

Fig. 12. Example of time-Frequency plane for osteoarthritis group (OA).

Fig. 8 - Fig. 12 show examples the time-frequency planes of the spectrograms for chosen one VAG signal from each group. Selection of the signals were conducted, considering the most characteristic artefacts, which appear in time-frequency planes.

The tests were performed for VAG signals, which were sampled at 10 kHz, the maximum number of samples of 61140, Hanning window $\gamma(t)$ with 300 samples and windows overlapping $\gamma(t)$ with 40 samples.

Analyzing of the above figures, below the time-frequency planes there are the VAG signal waveforms, on their left there are the frequency-mariginal conditions corresponding to the VAG signals spectrum, and above, there are energy decompositions over time (time boundary conditions). The energy, represented by the individual pixels at the time-frequency planes, has been normalized, considering the total energy of the signal.

The analysis of the time-frequency planes in individual cases shows the spectral content of waveforms as a function of time. The control group patient's plane (Fig. 8) is characterized by a relatively uniform width spectrum over the entire duration of the signal, reaching about 100 Hz. There are not visible any high frequency artefacts.

In cases of Ch I – Ch III (Fig. 9 – 11) and OA (Fig. 12), there are significant widenings (artefacts) of the frequency bands. In addition, it is also possible to see the periodicity of the spectral band widenings. These widths and the periodicity of the increase in width vary, depending on the type and stage of the disease. Analyzing time-frequency plane for Ch III (Fig. 11), results may be confusing. There appear 8 wide band components, what suggests 8 full flexion/extension cycles of the knee. In fact, there are 2 hondral lessions during one cycle.

Considering planes Ch I – Ch III (Fig. 9 – 11), it may be observed increasing of number of high frequency artefacts. Moreover, width spectrum and intensity of the artefacts increase too.

Comparing planes Ch I (Fig. 9) and OA (Fig. 12), it is visible, that number of high frequency artefacts are about the same, however the spectrum width and intensity is higher for OA.

[2] includes proposed power spectrum analysis in the two bands: 50 Hz - 250 Hz (Band 1) and 250 Hz - 450 Hz (Band 2). The energy content in these bands was proposed as a descriptor, determining: healthy state, the chondromalacia stage and osteoarthritis. Detailed statistical studies carried out in [2] show the dependence of energy values in the bands from the stage of disease.

Table 1 and Table 2 show statistical parameters of normalized energy values evaluated for Band 1 and Band 2. As stated above, the parameters refer to VAG signals, registered for 5 groups of patients (20 patients in each group). Fig. 13 and Fig. 14 graphically illustrate the results included in Table 1 and Table 2 respectively.

Table 1. Statistical parameters of normalized energy in 50 Hz – 250 Hz band – Band 1; N – Controls; CH I - Stage I of chondromalacia; CH II - Stage II of chondromalacia; CH III - Stage III of chondromalacia; OA – Osteoarthritis; Std – standard deviation; Q1 – 1st quartile; Q3 – 3rd quartile.

	Mean [-]	Std [-]	Median [-]	Q1 [-]	Q3 [-]
N	0.090	0.010	0.087	0.082	0.097
CH I	0.119	0.024	0.116	0.096	0.128
CH II	0.145	0.034	0.140	0.125	0.164
CH III	0.187	0.035	0.175	0.160	0.212
OA	0.187	0.050	0.192	0.161	0.224

Table 2. Statistical parameters of normalized energy in 250 Hz – 450 Hz band – Band 2. Abbreviations explained inTable 1.

	Mean [-]	Std [-]	Median [-]	Q1 [-]	Q3 [-]
N	0.011	0.006	0.009	0.004	0.006
CH I	0.024	0.010	0.024	0.011	0.017
CH II	0.039	0.016	0.037	0.020	0.026
CH III	0.065	0.022	0.061	0.035	0.046
OA	0.063	0.020	0.065	0.022	0.053

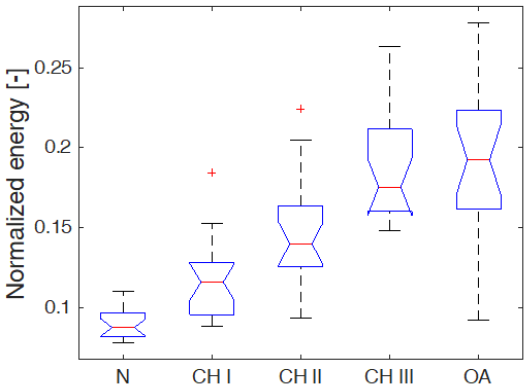

Fig. 13. Comparison of statistical parameters for Band 1. The horizontal line within the box indicates the median, box boundaries indicate the 1st and 3rd quartile respectively, whiskers indicate data not regarded as outliers — to a maximum of 3/2 times the height of the central box. Plus marks indicate outliers.

The following statistical parameters of normalized energy bands B1 and B2 were evaluated: mean, standard deviation (Std), median, 1st quartile (Q1) and 3rd quartile (Q3).

In analysing the above mentioned data one can observe statistically significant differences of mean and median between N, CH I, CH II and CH III or OA. The parameters are increasing.

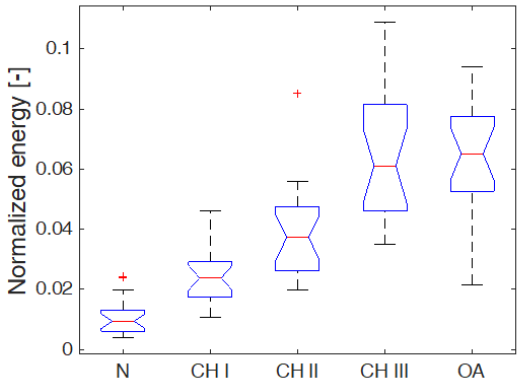

Fig. 14. Comparison of statistical parameters for Band 2. The horizontal line within the box indicates median, box boundaries indicate 1st and 3rd quartile respectively, whiskers indicates data that are not regarded as outliers - maximally to 3/2 times the height of the central box, plus marks indicate outliers.

Standard deviation is relatively high; however, central boxes, representing the central 50% of the data, increase significantly. For example the value of Q3 of CH I group is higher than the value of Q1 of N group, etc. This fact shows that the method of energy evaluation in Band I and Band 2, is statistically useful for the recognition of N, CH I, Ch II, Ch III and OA.

The whiskers, which represent the remaining data (without outliers), overlap one another. This indicates possible mistakes in group recognition. It can be observed especially in CH III and OA groups. That is why further research should be conducted in this area. For example, there should be changed the frequencies of boundaries for particular frequency bands (B1 and B2). On the basis of above, both parameters B1 and B2, have relatively similar quality of disease recognition.

However, to distinguish CH III from OA group, the time-frequency feature of artifacts may be considered.

On the Fig. 15 the time profiles of planes for N, Ch III, and OA (Fig. 8, 11 and 12 respectively) for a frequency of 250 Hz were shown.

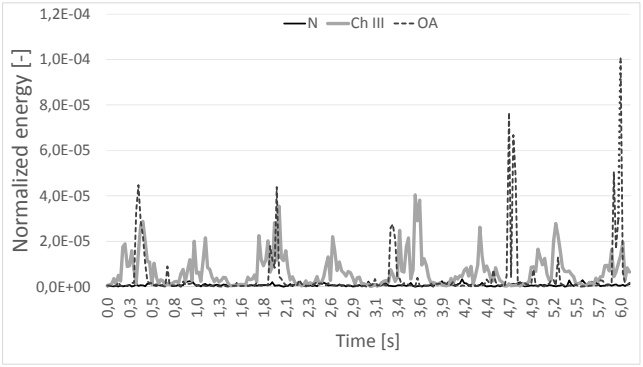

Fig. 15. Time profile for 250 Hz of time-frequency planes for patient from groups: N, Ch III and OA.

Time profile N is included for comparing purpose. It can be seen that time profile for CH III includes relatively long-term artefacts of moderate amplitude, while the profile for OA features several short-term high-amplitude artefacts. However, the total energy included in profile CH III is higher than OA. The time duration of the artefacts, connected with its width of spectrum, could provide the basis for another descriptor to distinguish disease CH III from OA more easily. This is a subject for further research.

Conclusion

The article presents two methods of examining the condition of the knee joint based on analysis of VAG signals. On the basis of the conducted studies, it can be concluded that the decomposition of current increments over time makes it possible to distinguish the stages of disease development. In case of analysis of VAG signal spectrograms, it is also possible to identify medical condition, but it is necessary to use test of plane time profiles in addition to descriptors defining spectrum energy in certain bands. There were stated, that further research on band parameters B1 and B2 should be carried out. Moreover, the use of the two analyses proposed in the article will allow for more reliable type identification and disease stage diagnosis.

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