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A novel attempt for diagnosing Outerbridge classification of articular cartilage damage via vibration transmission

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Abstract

This study as primary research to propose a non-invasive technique to diagnose the Outerbridge grade of cartilage damage by impact signals. A knee model was experimented with the novel attempt instead of a real knee. The knee model is made by a 3D model converted from magnetic resonance images (MRI) and then assembled by true scale and position. The impact signal is input from the calf and output from the thigh, and the absorption of the impact signal is contended differently by different Outerbridge grades of cartilage. The absorbed impact signals collected by sensors were time-frequency analyzed by continuous Gabor transform (CGT). In addition, the absorbed jerk signal is interpreted by the singular spectrum analysis (SSA) for its oscillation components. The analysis of the signals in this study found that the features derived have abilities to distinguish Outerbridge classification. Therefore, the proposed method can be considered for carrying the experiment onto real knees. This study provides a novel idea to make the diagnostic technique of cartilage damage efficient. Combined with the feature engineering and classification technique, it will help in the clinical diagnosis of knees, this study expects that the method can be applied not only to the diagnosis of the overall knee, but also that the method can diagnose more tiny areas in the early stages of the knee disorder.

Keywords: Cartilage damage, Impact signal, Knee model, Jerk signal, Outerbridge classification

1. Introduction

Osteoarthritis (OA) is a progressive disease. Usually, OA occurs in the knee joint because it supports almost the entire weight of the human body and provides motion during walking (Christensen et al., 2005). Because the knee joint is important and vulnerable to injury, the pathology of cartilage, which is the key to dynamic weight-bearing of the knee joint, is of interest to many studies. A relationship between cartilage damage and the grade of OA is shown (Bacon et al., 2020; Erhart-Hledik et al., 2015; Yoon et al., 2008). Consequently, a common belief is that when knee cartilage is injured by severe trauma or chronic incorrect gait, the normal balance between the damaged part of the biological repair and the healthy part of the injured cartilage is disturbed (Andriacchi et al., 2009; Wang et al., 2020; Wang et al., 2021). The imbalance eventually results in a localized loss of cartilage thickness, which further deteriorates knee OA.

The diagnosis of cartilage damage without medical equipment, such as palpation, is difficult. In addition, Bacon et al. argued that cartilage thickness loss is loosely associated with knee pain (Bacon et al., 2020). Therefore, it is difficult to uncover early signs of cartilage damage from pain symptoms. The non-invasive diagnosis of cartilage damage is mainly based on magnetic resonance (MR) imaging and ultrasound imaging (UI) (Koo et al., 2005; Naredo et al., 2009). This clinical diagnostic technique has tremendous advantages in terms of accuracy. However, owing to high operating and

maintenance costs diagnosing cartilage damage in the early stages is financially challenging . Vibrarthography (VAG) is a method, which infers the grade of knee disorder based on frictional vibrations between cartilages. The VAG technology is very economical and this study is partially inspired by it, however, VAG generates a noise along with the movement that can mask the real signal which makes it clinically inefficient (Gong et al., 2021; Gong et al., 2020; Gong et al., 2022) A reliable and inexpensive measurement technique for cartilage damage has not been applied yet in the clinical field. Therefore, this new technology for cartilage diagnosis is greatly needed.

Hence, we propose a new scheme to determine the cartilage damage grade based on changes in the acoustic model of cartilage. Studies of the acoustic model of cartilage are not uncommon but monitoring the time-frequency characteristics of regular-geometry cartilage phantoms or ultrasound images are more typical (Naredo et al., 2009; Nitta et al., 2019). This study used a real-scale entity model of the knee joint based on a 3D model drawn by MR images for vibration transmission experiments, which can be more symptomatic of cartilage damage. The 3D model is output and assembled into a knee model in which the cartilage is adjusted according to the Outerbridge Grading Systems (OGS), which is a grading standard for cartilage damage in the clinic (Bourke, 1988). A measurable impact signal transfers from the calf to the thigh, and the attenuation before and after passing through the cartilage indicates the cartilage damage level. Because the only variation in the entity model of the knee joint is the cartilage, then the loss of vibration transmission is variable in different OGS grades of cartilage. The cartilage can be considered as a viscoelastic material, so measuring and analyzing the vibration absorption in such a thin cartilage phantom is the focus of this study (Mak, 1986; Puppi et al., 2010).

Because the analysis is performed in extremely slightly changing signals, this study analyzed the absorbed vibration in both the acceleration and jerk dimensions. The continuous Gabor transform (CGT) is used for the time-frequency analysis in the acceleration dimension because it is not prone to resolution degradation (Rene Carmona et al., 1998). However, jerk is the differential of acceleration, contains richer information that humans can perceive, and is helpful in engineering (He et al., 2015; Lin et al., 2019). Finally, time-frequency analysis of the acceleration was combined with singular spectrum analysis of the jerk for cartilage damage grading (Golyandina et al., 2018).

The significance of this study is as a primary study of impact signals in clinical diagnostic studies related to knee cartilage damage. As primary research, the results of this study provide supporting evidence of the safety and efficacy of the proposed method in future clinical experiments. Hence, this new technology in this study will bring a new vision to the clinical diagnosis of the knee joint because it is affordable, highly robust, and requires no medical background.

2. Experiment

2.1 Construction of 3D knee joint models by MR images

MR images are usually in Digital Imaging and Communications in Medicine (DICOM) format . DICOM needs to be converted into a standard triangulated language (STL) file for engineering applications. In this study, 3D models of the femur, femoral cartilage, tibia, tibial cartilage, and meniscus in the knee joint were manually extracted from the DICOM drawing using 3D Slicer (Wang et al., 2020; Wang et al., 2021b). MR images were obtained from a female patient (76

Fig. 1 The 3D models manually extracted from MR images of the right knee joint in STL format.

years old) with mild OA knee, and the Tokyo Metropolitan University ethics committee permission number was H30-80. Subsequently, the knee joint parts were assembled in Netfabb (Autodesk), as shown in Fig. 1. In addition, the osteochondral knee and ligaments were not considered because of the MR image modeling and the scope of this study (Wang et al., 2020; Wang et al., 2021a).

2.2 Making of knee model

The knee model consists of two parts: the hard tissue part, bones; the soft tissue part is cartilage, meniscus, and other soft tissue. An ideal model knee joint needs to be in an extended position, and the cartilage and meniscus sandwiched between the femur and tibia, surrounded by layers of different soft tissues (Gong et al., 2020). However, if a model that is identical to human limb presents difficulties in assembling parts and sensors. Therefore, the knee model was simplified and made as follows.

2.2.1 The hard tissue part

The hard tissue part occupies approximately 90% of the transmission path. To make the hard tissue part more similar, the femur and tibia models were made cautiously in this study, as shown in Fig. 2.

Fig. 2 The process of making femoral and tibial models

Because the vibration signal passing through femur and tibia is unnecessary and a full-sized bone results in a higher center of gravity leading to greater baseline drift, the 3D models were cut off at 25 cm from the condyle of the femur and tibia. The unsmooth areas in the meshes of the femur and tibia obtained by MR imaging, were smoothed by Netfabb and output by the 3D printer (CR-10S PRO, Creality) for mold making. In addition, the bone tissue is in a honeycomb-like matrix structure that affects the bone mineral density (BMD) and is related to knee OA (Hulet et al., 2002). In this study, the Voronoi pipe was used to construct honeycomb-like structures in the bone tissue. Then, the printer created the Voronoi pipe and padded it into the wax mold and cast it with gypsum slurry (Yoshino-gypsum). Each hard tissue phantom was demolded after drying, of which 15% volume was polylactic acid (PLA, Tinmorry) Voronoi pipe and 85% volume was gypsum.

The BMD for the tibial model is 0.613 g / cm^2 and for the femoral model is 0.592 g / cm^2 , which is nearer to BMD of the lower limb bones of females aged 50-80 years with mild OA (Hulet et al., 2002).

2.2.2 The soft tissue part

Human soft tissues have a viscoelastic model to absorb vibration signals and are divided into categories by location. The meniscus and articular cartilage are summed up as one category and other soft tissues such as muscle and fat are summed up as the other category. The absorbed vibration of the former needs to be measured and analyzed in this study,

which is referred to as the target object (TO). The latter's absorbed vibration hinders this study, which is referred to as a futility object (FO).

The TO models were divided from top to bottom into femoral cartilage, meniscus, and tibial cartilage. Although the meniscus is sandwiched between the femoral and tibial cartilages, the cartilage-cartilage contact areas are expanded with meniscus movement. In addition, all of the cartilage-cartilage contact areas are widely perceived to risk becoming damaged in clinical diagnosis. In this study, the medial femoral cartilage was chosen for observation because cartilage-cartilage contact is more complex. (Cicuttini et al., 2005).

The medial femoral cartilage phantom is needed for deriving different pathological symptoms based on OGS in the original model's subsequent processing while being made as similar as possible. In OGS, the process of cartilage damage is first softening and swelling, then fissuring, and finally exposing the subchondral bone (Naredo et al., 2009), as shown in Fig. 3.

Fig. 3 The medial femoral cartilage damage by Outerbridge Grading Systems. The left side is a cross-section of medial femoral cartilage anatomy, and the right side is a front-view of the medial femoral cartilage 3D model. Grade 1: Softening and swelling; Grade 2: Fissures on the surface (diameter<1.5cm); Grade 3: Fissuring to the subchondral bone (diameter<1.5cm); Grade 4: Exposed subchondral bone.

Knee articular cartilage consists of collagen, proteoglycan, and water. It has a unique biomechanical model that can withstand a greater than bodyweight load without being broken (Lu and Mow, 2008; Laasanen et al., 2003). In this study, thermoplastic polyurethane (TPU, Pxmation), an elastic material with good compression and tensile resistance, was used to create a healthy cartilage phantom in this study. The Young's modulus of the TPU material is 2-5 MPa at room temperature, and that of human cartilage is 1.52 MPa (Franke et al., 2007; Lee et al., 2019). In this study, starting from grade 1, gelatin material in the damaged area replaced the healthy area on the medial femoral cartilage phantom. The damaged area is a projection on the cartilage of an ellipse with a semi-long axis of 10 mm and a semi-short axis of 5 mm. The replacement was designed on a 3D mesh but operated on the model. The composition of gelatin (Morinaga) is animal collagen, similar to human cartilage, but not as tough. The femoral cartilage phantom, as shown in Fig. 4, the Shore hardness of the model in the healthy area (white) is 39.8 and in the diseased area (pink) is 12.4.

Fig. 4 In the femoral cartilage phantom, the white area is healthy and the pink area is diseased. Grade 1: swelling and softening; Grade 2: fissures on the surface of the softened area; Grade 3: fissures are expanding, and the thickness is thinning. Grade 4: a part of the cartilage is completely losing, exposing subchondral bone.

The meniscus is the core component of knee joint movement and carries more stress than the cartilage during walking. However, the meniscus and cartilage material composition is almost same (Danso et al., 2014). Therefore, the tibial cartilage and meniscal model were made of the same material, thermoplastic polyurethane. As the experiments are planned to be performed under static posture with knee joint extension, the meniscal translocation can be ignored. However, as knee MR images are taken in the unloaded state, the meniscus deformation cannot be ignored (Wang et al., 2020).

To ensure the deformability of the meniscus is preserved while meniscus translocation is limited, a good strategy is to fix the meniscus and tibial cartilage together for a 3D printout. We combined the meniscus and tibial cartilage into one mesh based on the relative positions in the unloaded state. Subsequently, the printed tibial cartilage and meniscus phantom were separated partially along the contact surface of the meniscus and tibial cartilage with a heat knife (HS, Huanyu), leaving only one circle on the geometric center of the meniscus for fixation, as shown in Fig. 5.

Fig. 5 The lateral and medial meniscus are fixed to the lateral and medial tibial cartilage, respectively. The yellow area is the separated contact surface by the heat knife.

The fat and muscle (subcutaneous tissue) belonging to other soft tissues tightly wrap around the knee joint and support the body. While fat-muscle tissues can protect the knee, a thick layer of fat overloads the knee, causing damage to the cartilage and meniscus (Christensen et al., 2005; Gong et al., 2020). The fat-muscle tissues can be considered as a membrane stretched tightly over the cylindrical frame of the knee. The membrane impacting causes a surface vibration, which is called a two-dimensional wave. However, fat-muscle tissues are a typical viscoelastic body with thickness, and only extremely weak vibrations are caused by equilibrium perturbation. Since viscoelasticity attenuates the two-dimensional mechanical and vibration waves, covering the entire knee model with a fat-muscle tissue phantom is unwieldy (Kotzki et al., 1994). Therefore, the fat-muscle tissue phantoms as FO are retained only at the input and output points of the impact signal. Polyurethane gel (PU-gel, Proseven) is a skin-like material used as a fat-muscle tissue model. The thickness of the tissue models was different because the hit point was at the calf, and the measurement point was at the thigh. We used the muscle fat thickness of adult females as a baseline and cut the thickness down slightly to better match the fat-muscle tissue phantom of Asian females (Selkow et al., 2011; Tanner et al., 1981). The thickness of the fat muscle tissue model was set at 10 mm and 4 mm on the thigh and calf, respectively.

2.3 Assembly of knee model and sensors

2.3.1 Assembly of knee model

The knee model was assembled in a standing position, as shown in Fig. 6.

Fig. 6 Assembly of knee joint model

First, two 6 mm diameter holes were opened 10 mm below the femoral model cut-off surface in the sagittal and coronal planes. Two beams of the same diameter and length were then passed through the holes mentioned above. Two rubber bands with diameters of 3 mm connected the femoral model to the stands through the beam, and the femoral condyles were vertical to the ground due to gravity. In addition, the compressive stress between the femur and tibia can be changed by varying the number of hanging weights.

The standing position tibial model was inserted into a silicone-gel-filled box and placed directly below the femoral model after curing the silicone gel, which same as the tibia is fixed by the foot and ankle joint in standing position. After that, the fat-muscle tissue phantoms were secured with rubber bands to the femur and tibia models, respectively, at 15 cm from the knee joint contact surface. In addition, the boxes and stands were made heavy to ensure their stability.

The cartilage phantom and bone model were attached using self-tapping screws, as shown in Fig. 7. In this case, the femoral cartilage was fixed with three screws, and the medial tibial cartilage and lateral tibial cartilage were fixed using only one screw. Finally, when no weights are hanging from the beams, the stand is adjusted to a height using a film-type force sensor (FSR400, INTERLINK) where the femoral cartilage (damage area) is in contact with the meniscus, but the stress is close to 0 g/mm².

Fig. 7 In a, b, c, the red points are the connection points, and d is a photo of the cartilage phantom and the bone model in a fix.

2.3.2 Put on sensors to the knee model

In this study, the primarily used sensors were acceleration and force sensors. Among them, the aforementioned force sensors are mainly used to measure the stress caused by the load, while acceleration sensors are used to obtain vibration signals, which are the core signals. The sensor was placed on the knee model, as shown in Fig. 8.

Fig. 8 The diagram of sensors attached to the knee joint model. (1) and (2) illustrate the specifications of the sensors used in the experiments and the slave analog-to-digital conversion device numbers. (3) illustrate are the assembly diagram of the knee joint model and the sensors attachment diagram. (4) illustrate the spatial coordinate system of the patient's right knee.

The two force sensors (A2 and B2) are film-type force sensors clamped by the femoral cartilage and meniscus, which are used to measure the medial and lateral stresses. The stress signals were collected by an analog-to-digital converter (ADC2) (4224, Picoscope) and stored on a computer.

Conversely, four types of accelerometers are applied in this study. The impact hammer (086C03, PCB) is a hammer (A) with a built-in acceleration sensor that generates an impact signal by hitting an aluminum plate (20 mm × 35 mm × 5 mm) attached to the surface of the fat-muscle tissue phantom in tibial models. The impact hammer has an interchangeable impact chip in the head that can be hit to produce different frequency impact signals. In this study, an aluminum impact chip was used to obtain a higher-frequency input signal. Three accelerometers (353B16, PCB) belonging to the second type, that are connected to an adapter and fixed to the surface of fat-muscle tissue phantoms at the femoral model monitor output signals. The three acceleration sensors (B, C, and D) are perpendicular to each other in the spatial coordinate system, and one of them is parallel to gravity. To reduce circuit interference, four-channel signal conditioning (482C05, PCB) was used to filter and amplify the input and output signals, which were then stored by the ADC1 (4824, Picoscope) to the computer.

The remaining two types of accelerometers were prepared to collect reference signals. The first reference signal comes from the acceleration sensor (BW21SG2, FUJICERA) attached to the femoral model next to fat-muscle tissue phantoms. The sensor (E) is fixed to the femoral model by a double-sided adhesive in a direction parallel to gravity and compares the attenuation of the signal through the fat-muscle tissue phantom. The electrical charge is converted into voltage signals by the charge amplifier (CA201, FUJICERA) and then saved to the computer by ADC1 (4824, Picoscope).

The last type includes two triaxial acceleration sensors (KXR94-2050, Kionix) built-in amplifiers. These two sensors are fixed by a double-sided adhesive to the stand that hung the femoral model (F, G, H) and the box (A3, B3, C3) that holds the tibial model, respectively. They are used to detect the baseline drift from the hitting by a hammer and then saved to the computer by ADC1 and ADC3 (6254BD, Hantek).

In addition to the sensors, the weights were hung on the beams inserted into the femoral model. We mentioned earlier the no-load option, in which the stress between the meniscus and femoral cartilage is zero. On the flip side, the load option uses sixteen 15 g weights evenly hung on each beam branch. At this time, the cartilage and meniscus are deformed by compressive stress and the contact surface becomes larger. The reason for choosing 240 g as the load is the prosthetic material of healthy cartilage; diseased cartilage and meniscus are softer than the real one.

3. Signal acquisition and signal processing

The impact hammer hits an aluminum plate located in the tibial model, producing impact signals. The impact signals are picked up by accelerometers located at different positions of the knee model and converted to digital signals at a sampling rate of 20 kHz and a vertical resolution of 12 bits. However, the vertical resolution of the accelerometer leaving the knee model is only 8 bits, and a trigger control multiple channel.

3.1 Signal acquisition

When the experiment started, we first measured the stress of the femoral model with different Outerbridge grades under a 240 g load by the film-type force sensors. Because the knee joint model under load leads to displacement, which in turn brings about an imbalance of stresses in the medial and lateral zones, resulting in errors. Then, the medial and lateral stresses are balanced by adjusting the position of the weights on the beam. Calibration of the static baseline is required after all sensors are connected in a state of equilibrium stress.

Subsequently, the force sensors were removed, and the same experimenter used the impact hammer to hit the aluminum plate ten times with the same strength on different OGS grades of the femoral cartilage phantom, as shown in Fig. 4. The experiment with no load was the same as above, except that the stress measurement step was skipped.

Although the experiment in this study is similar to the modal analysis experiment, it is not the same. The differences are not only due to differences in equipment and methods, but also in human damage. Considering the cartilage as a viscoelastic object, which makes it difficult to observe the frequency response, it is a challenge to arrange enough acceleration sensors in such a narrow area of the knee, and to input a sufficiently strong impact signal to allow observation of the frequency response.

3.2 Signal processing

An ideal impact signal can be obtained when the hammer contacts the aluminum plate with an infinitely small duration, which can cause a constant amplitude in the frequency domain. Moreover, as an input signal, the impact signal is damped by a different part of the knee model during the transmission process. However, all parts were unchanged except for the femoral cartilage phantom in the whole knee model, and the femoral cartilage phantom was changed by OGS grade. Therefore, digital signal processing between the output and input signals makes it possible to obtain vibration signals absorbed by the cartilage with different OGS values. The signal processing process is illustrated in Fig. 9.

Fig. 9 The filtered input signal and the output signal are processed in the time domain, with the input signal in one-dimensional space and the output signal in three-dimensional space.

The signal processing can be described as follows: First, the linear trends in the raw signals are removed by the least-squares method (Borchers, 2021). Because the mass of the knee model is much smaller than the weight of a real person, hammering can cause interference from shaking. Subsequently, a fast Fourier transform combined with a Butterworth filter is required to remove the shaking in the frequency domain. These shakes were measured as reference signals by acceleration sensors attached to the stand and the box, and spectral energy was focused at 2-4 Hz. Because the real signal needs to be preserved as much as possible, a 6th order band-stop filter is applied to the input and output signals. Subsequently, to correct the delay, the maximum amplitude of the input signal was used as the target, and the output signals were shifted to the target in the time domain. Finally, to obtain the differences, the amplitude of the output signals

is reversed and interrupted to the same length as the input signal. Then, the output signals are added to the input signal to obtain three vibration signals absorbed in a three-dimensional space.

The signal processing in this study does not involve high-frequency noise reduction because the knee model is primarily static. There is only one band-stop filter that removes the baseline drift caused by the hammering.

3.3 Signal analysis

3.3.1 Time and frequency analysis of absorbed vibration signal

In signal analysis, time–frequency analysis is a body of techniques and methods used for characterizing and transient signals whose statistics vary over time. For normal time-frequency analysis, wavelet transform (WT) and Hilbert-Huang transform (HHT) are common choices for ensuring better time-domain resolution and frequency domain resolution of transient signals (Huang and Attoh-Okine, 2005; Gong et al., 2020). However, the calculated quantity was not friendly. In particular, a large number of samples, owing to the high sampling rate, require a large amount of computing time. To solve this problem, we extend to the continuous Gaber transform (CGT), based on the previously used short-time Fourier transform (STFT), to achieve the same time-frequency resolution with fewer calculations (Gong et al., 2021; Prabhu, 2018). The Gabor transform of a signal $x(t)$ is defined by the following equation:

$$G_x(t, f) = \int_{-\infty}^{\infty} e^{-\pi(\tau-t)^2} e^{-i2\pi f(\tau-\frac{t}{2})} x(\tau) d\tau \quad (1)$$

where the Gaussian function $e^{-\pi(\tau-t)^2}$ is regarded as a window function. Because its infinite range lacks practicality, its significance level distribution is often chosen as the new range. The equation can be simplified as:

$$G_x(t, f) \simeq \sqrt[4]{\sigma} \int_{t-\frac{1.9143}{\sqrt{\sigma}}}^{t+\frac{1.9143}{\sqrt{\sigma}}} e^{-\sigma\pi(\tau-t)^2} e^{-i2\pi f(\tau-\frac{t}{2})} x(\tau) d\tau \quad (2)$$

where σ is used to control the window width to hundred.

Because the CGT-based time-frequency analysis has good resolution in both the time and frequency domains, this study decided to use the distribution of the spectrum energy in the low-frequency zone as a characterization. That is, the duration of the component is more than 50% of the maximum spectral energy and below 2kHz.

3.3.2 Singular spectrum analysis of the absorbed jerk signal

The jerk is the rate at which the acceleration changes with respect to time, and it can be defined in differential terms as a vector.

$$\vec{j} = \frac{d\vec{a}}{dt} = \frac{d^2\vec{v}}{dt^2} = \frac{d^3\vec{s}}{dt^3} \quad (3)$$

Where, $\vec{a}$, $\vec{v}$, $\vec{s}$ are acceleration, velocity, displacement, respectively.

The jerk as a differential of acceleration is considered to have richer information, and the study also decided to analyze the absorption of the jerk signal by the knee model. Because jerk sensors are not commercially available as a standard product, we decided to use acceleration to calculate the jerk using the discrete derivative method with a gain value.

$$y(t_n) = K \left(\frac{x(t_n) - x(t_{n-1})}{T_s} \right) \quad (4)$$

where K is the gain value and T_s is a fixed discrete step size, both of which are set to one. However, because the differentiation is too sensitive to noise, an 11 order Savitzky–Golay (SG) filter is used before differentiation.

Although jerk has applications in aeronautical engineering and earthquake science, it is less analyzed by time-frequency analysis because of the lack of physical definition in classical mechanics (Manabe and Wakui, 2018; He et al., 2015). Therefore, this study analyzes the jerk signal with a singular spectrum to supplement the high-dimensional information not available in CGT analysis.

Singular spectrum analysis (SSA) is a practical technique for time-series analysis and forecasting. It is amazing as a

principal component analysis (PCA) for extracting information from time series. Slightly different from PCA, it performs better on short and nonstationary signals that contain more noise (Vitanov et al., 2008; Zhigljavsky, 2010). In this step, the SSA is used to extract the oscillation component of the jerk signal for the power around the highest oscillation point evaluation.

The basic SSA can be simply described as follows (Zhigljavsky, 2010). The obtained jerk signal $Y_N = (y_1, \dots, y_N)$ can be constructed as L -lagged vectors $Y_i = (y_i, \dots, y_{i+L-1})^T, i = 1, 2, \dots, K$ through a window of length L , where $K = N - L + 1$. Subsequently, these vectors can make up a trajectory matrix $\mathbb{Y}$. Subsequently, the eigenanalysis of matrix $\mathbb{Y}\mathbb{Y}^T$ (equivalently, the singular value decomposition of the matrix $\mathbb{Y}$) yields a collection of L eigenvalues and eigenvectors. A combination of these eigenvectors determines an r -dimensional subspace $\mathbb{L}^r$ in $\mathbb{R}^L, r < L$. The L -dimensional data $\{Y_1, \dots, Y_K\}$ were then projected onto the subspace $\mathbb{L}^r$. Some Hankel matrices $\mathbb{Y}^*$ are restructured by averaging over the diagonals, which approximates to $\mathbb{Y}$. Finally, the time series $Y_N^*(y^*, \dots, y_N^*)$, which has a one-to-one correspondence with the matrix $\mathbb{Y}^*$, provides an approximation of either the whole series Y_N or a particular component of Y_N .

Although there are four steps in the SSA algorithm, embedding, decomposition, grouping, and reconstruction, only two parameters, window length L and grouping index r , are involved. To extract the oscillation component better, we chose 50 as the window length and 1–3 as the grouping index because of the weaker weight correlation. Because the oscillation component of the jerk signal remains transient, the sum of squares of 50 steps before and after its highest oscillation point is used as the evaluation of power in this study, and the details are as follows.

$$m = \arg \max_{t_n} \{g(t_n)\} \quad (5)$$

$$p = \begin{cases} \sum_{j=1}^{100} [g(j)^2]; m \leq 50 \\ \sum_{j=m-50}^{m+50} [g(j)^2]; m > 50 \end{cases} \quad (6)$$

where $g(t_n)$ is the oscillation component drawn from the jerk signal $y(t_n)$ by the SSA. where p refers to the energy of the oscillation component. In this study, the arithmetic sum of the powers of the oscillation components in the three axes was used as an OGS grade feature.

3.3.3 Statistical analysis

Statistical analysis was performed for data analysis in this study. Owing to the small sample size in this study, we chose to use nonparametric statistics after the Shapiro-Wilk test found that it did not follow a regular distribution. The Friedman test was used for multiple comparisons in this study, and a confidence interval of 95% was set. In addition, the healthy group was set as the control group, and the other grades were designated as the test group for the Steel-Dwass test, again with 95% confidence intervals.

4. The result and discussion

4.1 Results and analysis

One set of acceleration signals is absorbed by the knee joint model, as shown in Fig. 10.

Apart from a slight difference in the amplitude strength, there is no significant difference in the vibration signal being absorbed in healthy cartilage and in the cartilage of grade 3, such as trend and sparseness. Therefore, some statistical features were computed to replace visual observation. The most commonly used features of biosignal are zero-crossing, kurtosis, and skewness, which have been successfully used in the feature extraction process with high efficiency (Gong and Hase, 2021). In the present study, the rate of directional change of the signal varies with the cartilage phantom by zero-crossing, and the slope of the signal also varied with the cartilage phantom, as determined by kurtosis and skewness. Although the statistical signal analysis results are insufficient to distinguish between cartilage damage grades, they provide some direction for moving forward.

Fig. 10 On the left is the absorbed acceleration signal in three directions by a knee joint model with healthy cartilage. On the right is the absorbed acceleration signal in three directions by a knee joint model with grade 3 cartilage.

After the CGT-based time-frequency analysis of the acceleration signals, the energy spectra were obtained. A typical energy spectrum is presented in Fig. 11. The energy spectrum was observed, and it showed the duration of the high-energy components is different in the low-frequency area. The area of a polygon constructed from the duration and frequency of the high-energy components seems to be a good classification feature.

Fig. 11 A typical CGT time-frequency energy spectrum of an acceleration signal in the z-axis direction. The frequencies in the red frame area are all below 2 kHz and the energies are all above 50% of the maximum energy.

The analysis of the energy spectrum area for all samples was statistically calculated and is shown in Fig.12. In the low-frequency region of the x-axis, the high-energy area decreased and then increased with the deterioration of cartilage damage. On the y-axis, the high-energy area of healthy cartilage was greater than that of the damaged cartilage, which was statistically significant except for grade 2. In the z-axis, the high-energy area of healthy cartilage was greater than that of grade 1 cartilage and was statistically significant. However, multiple comparisons performed on all samples in each axis showed no statistical significance.

This result does not follow the expectations of this study because we can see in Fig. 12 that the shapes of the dark enclosed areas can be used as a classification. However, the enclosed areas were inadequate for classification. One speculation is that perhaps the flat space of the energy spectrum consisting of time and frequency is restricted by Heisenberg's uncertainty principle of signal analysis. It is possible to start with a complexity aspect that may have enormous progress in the future. In addition, the instantaneous frequency also seems to have the potential to be used as a feature and deserves further investigation.

Fig. 12 The mean of the area of the high-energy spectrum in the low-frequency area at 3 directions for all signal samples. The error bars indicate the standard deviation. “n.s.” indicate not significant difference between the groups by Friedman test. Only “*” indicate significant difference between the control group and test groups by Steel-Dwass test.

Then, a set of jerk signals were computed to show in Fig. 13.

Fig. 13 The signal in the position is the acceleration signal in the x-axis direction on the knee joint model with grade 3 cartilage. The signal in the middle position is the filtered acceleration signal. The signal at the bottom position is the filtered jerk signal.

In Fig. 13, the raw acceleration signal contains high-frequency noise. If the acceleration signal without noise reduction is differentiated into a jerk signal, the high-frequency noise component will remain in the newly generated jerk signal and cause interference. Therefore, the jerk signal obtained after SG filtering can be used for the subsequent SSA analysis. The reason for not choosing the time-frequency analysis here is not only that the previous CGS analysis did not achieve the expected results, but also because of the inadequate physical definition of the jerk signal. After SSA analysis, the original jerk signal can be decomposed into trend, oscillation, and noise components. Because the jerk signal is

instantaneous, the trend component is meaningless and the noise component hinders the signal analysis, we only choose the oscillation component as the object of analysis. The oscillation components in the x-axis direction for a typical set of jerk signals are shown in Fig. 14.

Fig. 14 A typical set of oscillation components of the jerk signal in the x-axis direction.

It was observed that the oscillation component was perfectly extracted for each OGS grade. However, some noise components, almost negligible, are interspersed in the sub-signal. The sub-signals containing only oscillation components in the x -,y -, and z-axes were extracted by SSA. The power sums were calculated as described in a previous method. Statistical analysis was performed, as shown in Fig. 15.

These results were as expected. The classification ability of the proposed jerk signal oscillation component based in this study for different OGS-grade knee models is significant. The observation can see that the power of the oscillation component decreases with the deterioration of the damaged cartilage from grade 1 to grade 4. Although the variability

Fig. 15 The mean value of the power around the highest oscillation point of the jerk signal for different OGS grades cartilage phantom. The error bars indicate the standard deviation. “*” indicate significant difference between the groups by Friedman test. “***” indicate significant difference between the control group and test groups by Steel-Dwass test. “n.s.” indicate not significant difference.

between grade 1 and healthy subjects was not significant, there was a statistically significant difference with the other grades. Moreover, multiple comparisons performed on all samples showed statistical significance.

4.2 Limitations of this experiment

This study is an attempt to diagnose knee cartilage loss using impact signals based on a real-scale knee joint model with different OGS-grade cartilage phantoms. Despite the results achieved in this study, there are limitations in the fabrication of the knee joint model.

First, the models in this study were built with many different materials, especially soft tissues, using both hydrated (damage part) and non-hydrated (health part) materials in cartilage phantoms. However, this option has both advantages and disadvantages. The advantages are that non-hydrated materials have stable size, softness and elasticity, while hydrated materials can adjust softness and elasticity according to different OGS-grade. The disadvantage is that the existence of water molecules varies greatly in the material structure, and there is a high risk that the change in the impact signal depend on the material structure.

Second, limitations were encountered in the assembly of the model. The real knee joint functions as a hinge structure with both mobility and stability at different flexion angles. However, the study only tried to analyze the impact signal when the femur and tibia were vertical to the ground at the same time (with load). In addition, the mechanical connection between the meniscal phantom and the cartilage phantom is also distinct from the anatomical knee joint. These will need to be refined in future studies.

Third, the impact signal was measured in a standing position on this model, but the participants would constantly seek to balance the center of gravity while standing, resulting in a contact surface of the knee joint changing. In future experiments, participants will be in the prone position for the experiment. A constant pushing force is applied to the foot of each individual to ensure that all contact conditions are performed under a constant load.

Fourth, many components are omitted from this knee model in 3D digital model and solid model building due to the current technical situation. These include, ligaments, synovial layer (of joint capsule), fibrous layer (of joint capsule) and synovial fluid (in joint cavity). And the model was also not covered with soft tissue. In particular, a joint cavity filled with negative pressure and synovial fluid may pose a barrier to clinical application of this study in future.

Conversely, although neither the proposed model nor the proposed method is perfect in primary research stage, it still holds great promise. Because this active biomedical signal is far superior to traditional medical imaging in terms of cost and usability. Along with the continuous research, the aforementioned task will also be a constantly being cleared in future stages of this study.

5. Conclusion

The considerable pain caused by knee OA in patients led us to focus on non-invasive diagnostic techniques for knee cartilage damage. Subsequently, a hypothesis is proposed for determining the OGS grade of cartilage damage by impact signals and experimented on a hand-made knee model for verification. Furthermore, the CGT-based time-frequency analysis and SSA-based analysis of the jerk signal could find some features that could be characterized as different OGS grades of cartilage damage. These features give confidence to the present study in transferring this hypothesis to a real knee cartilage diagnosis.

Although this study as primary research proposes a framework for the application of impact signals as active biomedical signals on knee joint models, there are many clinical topics that need to be addressed in the future. As the research progresses, the biomedical signal will also become a diagnostic method alongside medical imaging.

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