



Infrared spectroscopy is suitable for objective assessment of articular cartilage health



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ABSTRACT

Objective: To evaluate the feasibility of Fourier transform infrared attenuated total reflectance (FTIR-ATR) spectroscopy to detect cartilage degradation due to osteoarthritis and to validate the methodology with osteochondral human cartilage samples for future development towards clinical use.

Design: Cylindrical ($d = 4$ mm) osteochondral samples ($n = 349$) were prepared from nine human cadavers and measured with FTIR-ATR spectroscopy. Afterwards, the samples were assessed with Osteoarthritis Research Society International (OARSI) osteoarthritis cartilage histopathology assessment system and divided into two groups: 1) healthy (OARSI 0–2) and 2) osteoarthritic (OARSI 2.5–6). The classification was done with partial least squares discriminant analysis model utilizing cross-model validation. Receiver operating characteristics curve analysis was performed and the area under curve (AUC) was calculated.

Results: For all samples combined, classification accuracy was 73% with AUC of 0.79. Femoral samples had accuracy of 74% and AUC of 0.77, while tibial samples had accuracy of 66%, and AUC of 0.74. Patellar samples had accuracy of 84% and AUC of 0.91.

Conclusions: The results indicate that FTIR-ATR spectroscopy can differentiate between healthy and osteoarthritic femoral, tibial and patellar human tissue. If combined with a fiber optic probe, FTIR-ATR spectroscopy could provide additional objective intraoperative information during arthroscopic surgeries, which could improve clinical outcomes.

1. Introduction

Articular cartilage, the highly specialized connective tissue covering the ends of bones in diarthrodial joints, enables the near frictionless movement of joints [1]. Articular cartilage is avascular and aneural and, hence, has limited self-repair capacity [1]. Cartilage cells, i.e., chondrocytes, occupy 1–3% of total cartilage volume [2]. Chondrocytes are surrounded by water and extracellular matrix (ECM), which is a complex network of collagen fibers and proteoglycans [2].

Injuries to articular cartilage present an exceptionally challenging medical problem due to lack of the tissue self-regenerative capability [3]. Moreover, untreated cartilage injuries may develop into osteoarthritis (OA) with symptoms like swelling, joint pain and impaired mobility. OA is the most common chronic joint disease. Globally, the socio-economic burden of OA is rising due to the ageing population and obesity [4]. The annual cost of OA range between 1330 and 10,452 euros per capita in Europe [5]. Currently, there is no cure for OA, although numerous repair procedures exist for treating knee joint injuries. The goal of

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cartilage repair surgery is to restore the cartilage tissue, and it is typically carried out during arthroscopy [3]. The effectiveness of the repair procedures relies on an accurate diagnosis of the severity and extent of the articular cartilage damage [6]. At present, orthopaedic surgeons rely on visual assessment and manual probing to estimate cartilage health during the arthroscopic joint repair surgeries [7]. Thus, the current arthroscopic assessment of cartilage is highly subjective and has poor reproducibility [8,9].

Fourier transform infrared (FTIR) spectroscopy, a popular type of vibrational spectroscopy, is based on molecular vibrations of investigated material, and it can provide specific information on tissue biochemical composition without any sample processing [10,11] (Fig. 1). There are studies showing that an FTIR spectrometer can be coupled with an attenuated total reflectance (ATR) based fiber optic probe to enable *in vivo* measurements [12,13]. Fiber optic FTIR spectra of degenerated tibial human articular cartilage have been shown to correlate with Mankin grade (histological assessment of cartilage) [14] and Collins grade (macroscopic assessment of cartilage) [15]. Moreover, multivariate data analysis of FTIR spectra can differentiate between the type of collagen, *i.e.* type I or II, in connective tissues [16]. Consequently, these results suggest that FTIR spectroscopy could provide objective information about cartilage tissue health during arthroscopy to help making better-informed decisions and, thus, potentially improve surgery outcomes.

The aim of the present study was to evaluate the feasibility of FTIR-ATR spectroscopy for assessing articular cartilage health. Earlier FTIR-ATR studies on human tissue have been limited to the study of tibial cartilage [14]. In contrast, more versatile sample set used in this study includes tibial, femoral, and patellar cartilage. A Multivariate discriminant model was built to classify the cartilage FTIR spectra into relatively intact and degraded classes according to Osteoarthritis Research Society International (OARSI) histopathological grading [18].

2. Methods

2.1. Study design and experimental samples

The sample set consisted of a total of 349 samples which were extracted from both knees of 9 human cadavers. The complete study design is described in the flowchart presented in Fig. 2. Ethical permission was obtained from Ethics Committee of Northern Savo prior to performing the study, permission number 123/2015 (58/2013). The samples were prepared by drilling cylindrical ($d = 4$ mm) osteochondral plugs with a dental drill from central locations of femoral, tibial, and patellar cartilage. After extraction, the sample plugs were immersed in phosphate buffered saline (PBS) and deep frozen at -80 °C for storage.

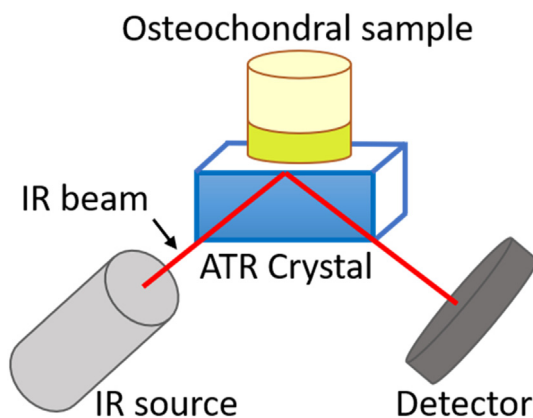


Fig. 1. A schematic representation of Fourier transform infrared (IR) attenuated total reflection (ATR) measurement setup.

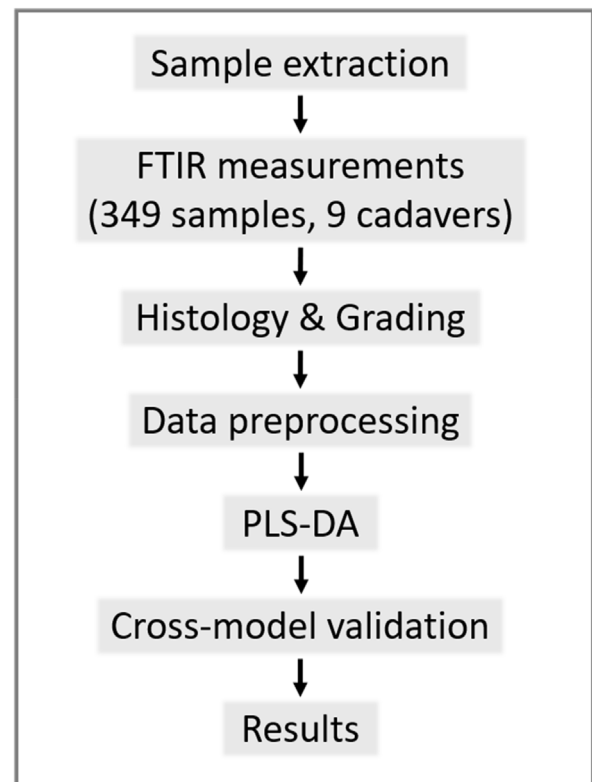


Fig. 2. Study design flowchart showing the number of Fourier transform infrared (FTIR) measurements. The analysis method utilized was partial least squares discriminant analysis (PLS-DA).

2.2. Fourier transform infrared spectroscopy

Prior to FTIR spectroscopic measurements, deep frozen samples were left to thaw at room temperature for 30 min. Defrosted samples were subsequently attached with instant glue (Cyanoacrylate, Loctite 401, Henkel Corporation) from bone to plastic petri dishes to ensure easier clamping of the tissue to enable good contact with the ATR sampling cell (Fig. 1).

Spectra were recorded with a Bruker Alpha HR spectrometer (Bruker Optics GmbH, Ettlingen, Germany) equipped with a globar mid-IR source and a deuterated triglycine sulfate (DTGS) detector. The Bruker OPUS 8.1 (Bruker Optics GmbH, Ettlingen, Germany) spectroscopy software was used for data acquisition and instrument control. The spectrometer was equipped with a Bruker Platinum ATR sampling cell (Bruker Optics GmbH, Ettlingen, Germany). The cell is composed of a single reflection diamond ATR crystal embedded in tungsten carbide which provides excellent inertness towards biomedical samples. Further, the Platinum ATR cell contained an adjustable pressure clamp that facilitated adjustment of an optimum contact pressure for reproducible acquisition of FTIR-ATR spectra. During measurement, the osteochondral plugs were immersed in PBS to avoid dehydration and to maintain a physiological environment. For each spectrum, 128 scans were averaged. The ATR crystal was cleaned with isopropanol and background was measured in air between each sample measurement. Spectra were recorded within a spectral window of 4000 cm^{-1} to 600 cm^{-1} at a spectral resolution of 2 cm^{-1} . Each sample was measured three times except for one sample for which one replicate is missing.

2.3. Histology

The samples were fixed in formalin and decalcified with 5% EDTA solution after FTIR spectroscopic measurements. Following dehydration, the samples were embedded in paraffin for histology. Thereafter, 3 μm

thick sections were cut and stained with Safranin O. These histological sections were evaluated according to the OARSI grading system [18], which grades the lesion depth to assess the severity of OA with grades ranging from 0 (healthy) to 6 (severe OA with bone exposed). In this study, randomly ordered and blind-coded sections were scored by three graders first independently, and afterwards a consensus grade was decided by uniform agreement. The grades were then pooled to form a sample set with largely intact tissue (OARSI grade: 0–2) and another sample set with clear surface damage, such as fissures and loss of cartilage matrix (OARSI grade: 2.5–6).

2.4. Data analysis

Spectra from samples with insufficient cartilage contact to the ATR crystal were excluded by removing all spectra with absorbance less than 0.05 at 1240 cm^{-1} . This removed 22 spectra in total. The remaining 1,024 spectra were included in further analysis. Pre-processing by weighted multiplicative signal correction (MSC) [19,20] was applied. Regions of 1800–1780 cm^{-1} and 900–800 cm^{-1} were up-weighted by 15 to mitigate baseline effects. Afterwards, the spectral range was truncated to 1720–900 cm^{-1} .

A partial least squares discriminant analysis (PLS-DA) classifier was used for discriminating the spectra into healthy (OARSI 0–2) and osteoarthritic (OARSI 2.5–6) groups. In PLS-DA, latent variables (i.e. PLS components) are calculated from independent (spectra) and dependent (sample groups, dummy variable: 0 (healthy) and 1 (osteoarthritis)) variables by maximising the covariance between the two variable sets. This reduces the dimensionality of the data and, thus, the effect of the multi-collinearity problem [21]. Models with up to 20 PLS components were calculated, and the model with the smallest number of PLS components, where the error is within 5% of the true minimum across all 20 PLS components, was selected as the final model. The cut-off for classification between healthy and osteoarthritic groups was 0.5.

Cross-model validation (CMV) [22] was used to reduce the possibility of overfitting and to check the stability of the results. For each CMV loop, samples from one cadaver at a time were taken out completely from the training set and used as the test set. The remaining training set was subjected to a leave-one cadaver-out cross validation to optimize the model parameters (number of PLS components). The resulting PLS-DA model was then used for classifying the samples of the test set. This was repeated 9 times to classify the samples of all cadavers. The number of PLS components for each CMV step is shown in Table 1. Accuracy, sensitivity and specificity of the classification was calculated.

2.5. Statistical analysis

To evaluate PLS-DA model's performance, receiver operating characteristics curve analysis was obtained and area under curve (AUC) was calculated utilizing MATLAB built-in function `perfcurve`.

Intraclass correlation coefficient (ICC) was calculated to determine the reliability of OARSI grading between the three assessors. ICC was calculated from two-way random effects analysis of variance, with

absolute agreement [23]. Inter-observer variability between the three observers showed ICC of 0.82.

3. Results

Mean FTIR-ATR spectra of the fingerprint region (1720–900 cm^{-1}) of the two sample groups are presented in Fig. 3 and the spectral difference between groups is shown in Fig. 4. Healthier group shows higher absorbance in most of the prominent bands, such as the amide I (1700–1600 cm^{-1}), amide II (1580–1490 cm^{-1}) and amide III (1300–1200 cm^{-1}). Collagen related peaks at 1458 cm^{-1} , 1378 cm^{-1} and 1338 cm^{-1} also show slightly higher absorbance in the healthier group. In the carbohydrate region, C–O stretch at 1165 cm^{-1} shows higher intensity in healthier groups, with smaller variation across the region from 1100 cm^{-1} to 1000 cm^{-1} .

PLS-DA was used for classifying the FTIR-ATR cartilage spectra into healthy and diseased groups. CMV accuracy was 72.8% and AUC was 0.79 for all samples combined. We also investigated the results by selecting the samples from femur, tibia, and patella separately. Classification of femoral samples had 73.6% accuracy and 0.77 AUC, tibial samples 66.0% accuracy and 0.74 AUC, while classification of patellar samples had 83.7% accuracy and 0.91 AUC. Confusion matrices for all samples combined and for each of the anatomical locations separately are shown in Table 2, while CMV accuracies and AUCs are shown in Table 3. For all samples combined, accuracy, sensitivity, and specificity for each step of the cross-model validation is shown in Fig. 5. The accuracy and sensitivity was notably worse for step #1 compared to rest of the CMV steps.

4. Discussion

The aim of this study was to evaluate the feasibility of FTIR-ATR spectroscopy for assessment of human cartilage health. In contrast to earlier studies, we included cartilage from joint surfaces of multiple bones, i.e., tibia, femur, and patella. A good overall classification accuracy of 72.8% was obtained with a PLS-DA model. This is a promising result considering the limited amount of data for modelling in the current study and conservative method applied to validate the developed PLS-DA model. The present results indicate that objective spectroscopic approach could provide an improvement over the currently used subjective methods, which have a limited accuracy [9].

Previous FTIR-ATR spectroscopic studies have used Mankin scoring and Collins grade as the reference classification methods. Mankin score is a histological score that considers progressive features of OA (i.e., lesion depth), but also features related to disease activity, such as cellular features and proteoglycan depletion. In contrast, Collins grade is a macroscopic grade that does not capture early tissue-level changes. In our study, we decided to use the OARSI histological grading as it is designed to reflect only the progression of OA [18]. In classification analysis, we

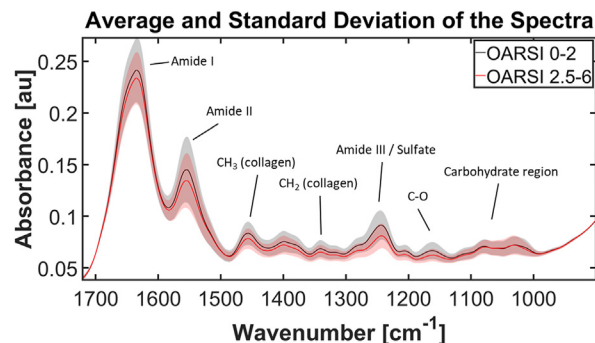


Fig. 3. Average spectrum (line) and standard deviation (shaded area) for healthy (OARSI 0–2) (black/grey) and osteoarthritic (OARSI 2.5–6) (red) groups.

Table 1

Number of partial least squares (PLS) components in each cross-model validation (CMV) step.

CMV step number	Number of PLS components
1	7
2	11
3	9
4	8
5	10
6	8
7	10
8	6
9	9

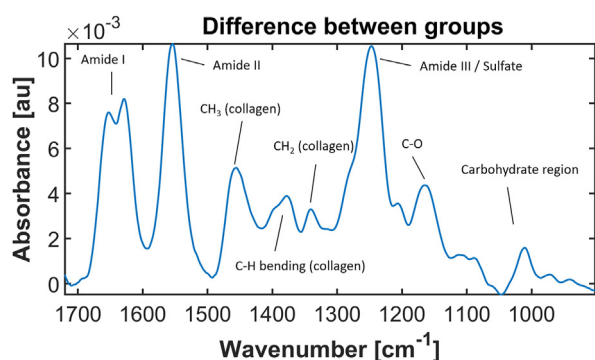


Fig. 4. Difference spectra between healthy (OARSI 0–2) and osteoarthritic (OARSI 2.5–6) groups.

Table 2

Confusion matrices of the cross-model validated partial least squares discriminant analysis (PLS-DA) models for samples from each anatomical location and all locations combined. The number of spectra is shown inside the brackets in each cell.

Anatomical location		Diseased (predicted)	Healthy (predicted)
Femur	Diseased (true, 237)	74% (176)	26% (61)
	Healthy (true, 373)	27% (100)	73% (273)
Tibia	Diseased (true, 171)	73% (124)	27% (47)
	Healthy (true, 120)	43% (52)	57% (68)
Patella	Diseased (true, 102)	88% (90)	12% (12)
	Healthy (true, 21)	38% (8)	62% (13)
All samples combined	Diseased (true, 510)	76% (390)	24% (120)
	Healthy (true, 514)	31% (160)	69% (354)

Table 3

Cross-model validation (CMV) accuracy and area under curve (AUC) for receiver operating characteristics curve of the partial least squares discriminant analysis (PLS-DA) models for samples from each anatomical location.

Sample location	CMV Accuracy	AUC
Femur	73.6%	0.77
Tibia	66.0%	0.74
Patella	83.7%	0.91
All combined	72.8%	0.79

chose a cut-off of grade 2.5 or higher for damaged cartilage. The reason for this selection is that OARSI grade 2.5 or higher reflects extensive collagen network disruption at the surface layers, which means that the disease has progressed beyond the point of intrinsic ability for cartilage tissue to repair itself. With this classification, the spectral differences between the relatively intact samples and damaged samples can be seen especially in the amide I ($1700\text{--}1600\text{ cm}^{-1}$), amide II ($1580\text{--}1490\text{ cm}^{-1}$) and amide III ($1300\text{--}1200\text{ cm}^{-1}$) regions. This indicates disintegration of the collagen matrix network at the surface of the tissue. The finding is further confirmed in collagen related peaks at 1458 cm^{-1} , 1378 cm^{-1} and 1338 cm^{-1} , which also show decreased intensity in group with higher OARSI grades. The change at 1338 cm^{-1} is especially associated with decreased integrity of type II collagen [24,25]. Furthermore, differences between the groups can be seen in the carbohydrate region ($1180\text{--}1000\text{ cm}^{-1}$), and in the sulfate band at about 1245 cm^{-1} , which both are associated with the changes in the proteoglycan contents [26]. While these changes can be visually seen in the average and difference

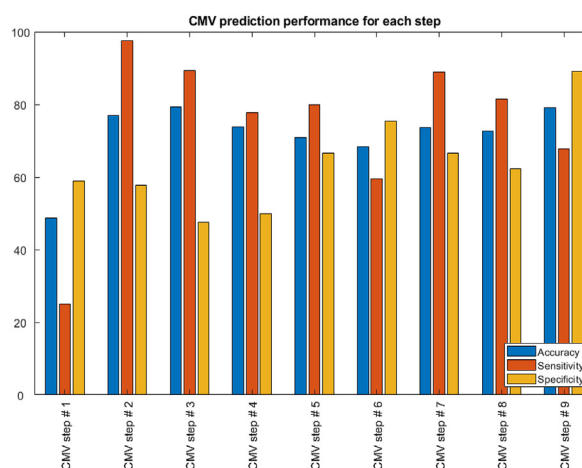


Fig. 5. Accuracy, sensitivity, and specificity of the partial least squares discriminant analysis (PLS-DA) model for each validation step of cross-model validation.

spectra, they might not be statistically significant by themselves, thus requiring the utilization of the multivariate methods.

PLS-DA classifiers are routinely used in spectroscopic analysis of biological tissues [16,27–30]. The validation for classification methods used in previous publications are not always clear as it is not necessarily mentioned whether the technical replicates of the same specimen or specimen extracted from the same individual are used in both the training and the test sets. We chose to validate the PLS-DA model using CMV to reduce the chance of overfitting. In our analysis, we separated the cadavers so that all samples extracted from one cadaver are used as the test samples in a single CMV step. In other words, samples of the same cadaver are not simultaneously present in training and test sets. This provides more conservative results, but also gives us confidence that the developed model generalizes better for unseen data. The present results indicate that FTIR-ATR spectroscopy has potential to be utilized as an objective tool during arthroscopy and give more confidence for surgeons during intraoperative decision making. Fiber optic spectroscopic methods have shown promise towards clinical use as summarised in recent review paper [11], and our study is one more step towards applications for cartilage health assessment.

The present study is limited by the relatively low number of samples. Furthermore, the uneven distribution of OARSI grades made more fine-grained classification analysis with multiple different OARSI grades unfeasible. In particular, the number of cadavers in the dataset is critical for generalization of the model. Fig. 5 shows that when testing the performance of the models on samples from certain cadavers, the performance of the model can vary. For example, when testing the model with cadaver #1 samples as the test set, the accuracy and sensitivity are notably worse compared to other CMV folds where other cadavers were utilized as independent test sets. Lower sensitivity in this case indicates that the model predicted relatively more of the degenerated samples as healthy. It is possible there is some biological reason behind this, and thus, increasing the number of cadavers would capture the biological variation between the individuals better and, therefore, result in more robust models. However, the overall performance of the PLS-DA model is good, as the accuracy and AUC were 72.8% and 0.79, respectively. Compared to earlier studies, we also investigated the location-based differences in this study. While the patellar samples showed high accuracy and AUC, the results are biased since 102 out of 123 samples had OARSI grade higher than 2. Femoral samples show similar performance to the overall model, which is most likely due to the majority of the samples being from femur. Tibial samples show slightly poorer performance at only 66.0% accuracy and 0.74 AUC. The healthier samples from tibia seemed to be more likely to be classified as degenerated: 43% or 52 out of 120 OARSI 0–2 grade

samples were misclassified as OARSI 2.5–6 group samples in the tibial group. The result is likely explained by tibial cartilage having slightly different composition and structure compared to the femoral cartilage [31]. Thus, the tibia samples are more easily misclassified as the majority of the samples used for training the model were from femoral cartilage.

Another limitation related to the technique itself is the low penetration depth (few micrometres) of infrared light in FTIR-ATR sampling. Thus, the method is limited to the analysis of cartilage surface. However, this does not prevent the detection of cartilage degeneration. FTIR-ATR spectroscopy is highly sensitive to changes in the molecular composition, and even small alterations in the constituents of the cartilage surface can be detected. The composition of cartilage changes at different depth of the tissue, and FTIR imaging studies of histological sections have shown that there are major differences between the spectra acquired from different depths [24,25]. If the degeneration has progressed so far that the original surface is no longer present, the classification models could also incorporate the depth-related spectral differences in addition to the degeneration related changes in classifying the cartilage FTIR-ATR spectra. It is also possible that PBS content remaining within the tissue during measurements varies between healthier and more degenerated samples. Thus, some of the absorbance differences in the Amide I region could be attributed to that effect. ATR technique relies on stable contact between the surface of the tissue and the ATR crystal. If the surface is degenerated enough that cartilage is missing, measurements will not be reliable. Since this amount of degeneration is easily seen by the surgeon, it does not affect potential clinical use.

As a summary, current methods, such as the International Cartilage Regeneration & Joint Preservation Society (ICRS) classification, for clinical arthroscopic evaluation of cartilage health are subjective and show relatively poor reproducibility [9,32]. Fiber optic FTIR-ATR spectroscopy during arthroscopic joint surgeries could provide valuable information during the surgery and allow objective measures to guide the surgeon. Highly damaged cartilage can be visually seen during arthroscopy, but objective methods for assessing the extent of damaged regions might help guide the extent of interventions taken by the surgeon. Identifying regions with early-stage tissue degeneration, which cannot be seen with current methods, could be important for prevention of OA. Our findings indicate that FTIR-ATR spectroscopy is a promising method for objective assessment of cartilage health.

Contributions

Vesa Virtanen: Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Valeria Tafintseva:** Methodology, Software, Validation, Data curation, Writing –

review & editing. **Rubina Shaikh:** Investigation, Writing – review & editing. **Ervin Nippolainen:** Investigation, Data curation, Writing – review & editing. **Julian Haas:** Investigation, Writing – review & editing. **Isaac Afara:** Writing – review & editing, Funding acquisition. **Juha Töyräs:** Resources, Writing – review & editing, Supervision, Funding acquisition. **Heikki Kröger:** Investigation, Writing – review & editing. **Johanne Solheim:** Software, Data curation, Writing – review & editing. **Boris Zimmermann:** Software, Writing – review & editing. **Achim Kohler:** Resources, Supervision. **Boris Mizaikoff:** Resources, Writing – review & editing. **Mikko Finnilä:** Writing – review & editing. **Lassi Rieppo:** Conceptualization, Methodology, Software, Validation, Investigation, Writing – review & editing. Supervision, Funding acquisition. **Simo Saarakkala:** Conceptualization, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Role of the funding source

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All authors declare no conflicts of interest.

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References

- [1] A.J. Sophia Fox, A. Bedi, S.A. Rodeo, The Basic Science of Articular Cartilage: Structure, Composition, and Function. *Sports Health* [Internet], 2009 Nov 2 [cited 2021 Jan 19];1(6):461–8. Available from: <http://journals.sagepub.com/doi/10.1177/1941738109350438>.
- [2] Y. Luo, D. Sinkeviciute, Y. He, M. Karsdal, Y. Henrotin, A. Mobasheri, P. Önnérjörd, A. Bay-Jensen, The Minor Collagens in Articular Cartilage [Internet]. Vol. 8, Protein and Cell, Higher Education Press, 2017 [cited 2021 Jan 19]. pp. 560–72. Available from: <https://link.springer.com/article/10.1007/s13238-017-0377-7>.
- [3] A.J. Sutherland, G.L. Converse, R.A. Hopkins, M.S. Detamore, The bioactivity of cartilage extracellular matrix in articular cartilage regeneration, *Adv Health Mater* [Internet] (2015), <https://doi.org/10.1002/adhm.201400165>. Jan 1 [cited 2021 Jan 19];4(1):29–39. Available from: .
- [4] A.A. Kiadaliri, L.S. Lohmander, M. Moradi-Lakeh, I.F. Petersson, M. Englund, High and Rising Burden of Hip and Knee Osteoarthritis in the Nordic Region, 1990–2015. *Acta Orthop* [Internet], 2018. Mar 4 [cited 2021 Jan 19];89(2):177–83. Available from: <https://www.tandfonline.com/doi/full/10.1080/17453674.2017.1404791>.
- [5] The economic weight of osteoarthritis in Europe - *Medicographia* [Internet], Jan 19. Available from: <https://www.medicographia.com/2013/10/the-economic-weight-of-osteoarthritis-in-europe/>, 2021.
- [6] E.B. Hunziker, Articular cartilage repair: basic science and clinical progress. A review of the current status and prospects, *Joint J* 10 (6) (2002) 432–463.
- [7] M. Brittberg, C.S. Winalski, Evaluation of cartilage injuries and repair [cited 2021 Jan 19], in: *Journal of Bone and Joint Surgery - Series A* [Internet], Journal of Bone and Joint Surgery Inc., 2003, pp. 58–69. Available from: <https://pubmed.ncbi.nlm.nih.gov/12721346/>.
- [8] B.H. Brismar, T. Wredmark, T. Movin, J. Leandersson, O. Svensson, Observer reliability in the arthroscopic classification of osteoarthritis of the knee, *J Bone Joint Surg Br* 84-B (1) (2002 Jan) 42–47.
- [9] G. Spahn, H.M. Klinger, M. Baums, U. Pinkepank, G.O. Hofmann, Reliability in arthroscopic grading of cartilage lesions: results of a prospective blinded study for evaluation of inter-observer reliability, *Arch Orthop Trauma Surg* 131 (3) (2011) 377–381. <https://link.springer.com/article/10.1007/s00402-011-1259-8>.
- [10] L. Rieppo, J. Töyräs, S. Saarakkala, Vibrational spectroscopy of articular cartilage, *Appl Spectrosc Rev* 52 (3) (2017) 249–266. <https://www.tandfonline.com/doi/full/10.1080/05704928.2016.1226182>.
- [11] W. Querido, S. Kandel, N. Pleshko, N.L.M. (Medline [Internet], Applications of Vibrational Spectroscopy for Analysis of Connective Tissues, vol. 26, Molecules, Basel, Switzerland), 2021, <https://doi.org/10.3390/molecules26040922> [cited 2021 May 6]. p. 922. Available from: <https://www.mdpi.com/journal/molecules>.
- [12] Q.B. Li, Z. Xu, N.W. Zhang, L. Zhang, F. Wang, L.M. Yang, J.S. Wang, S. Zhou, Y.F. Zhang, X.S. Zhou, J. Sen Shi, J.G. Wu, In vivo and in situ detection of colorectal cancer using Fourier transform infrared spectroscopy, *World J. Gastroenterol.* 11 (3) (2005) 327–330. Jan 21.
- [13] A. Ring, V. Schreiner, H. Wenck, K.P. Wittern, L. Küpper, R. Keyhani, Mid-infrared spectroscopy on skin using a silver halide fibre probe in vivo. *Ski Res Technol* [Internet], Feb 1 [cited 2021 May 6];12(1):18–23. Available from: <https://onlinelibrary.wiley.com/doi/full/10.1111/j.0909-725X.2006.00130.x>, 2006.
- [14] A. Hanifi, X. Bi, X. Yang, B. Kavukcuoglu, P.C. Lin, E. Dicarolo, R.G. Spencer, M.P.G. Bostrom, N. Pleshko, Infrared fiber optic probe evaluation of degenerative cartilage correlates to histological grading [Internet], *Am. J. Sports Med.* 40 (12) (2012) 2853–2861, <http://journals.sagepub.com/doi/10.1177/0363546512462009>.
- [15] P.A. West, M.P.G. Bostrom, P.A. Torzilli, N.P. Camacho, Fourier transform infrared spectral analysis of degenerative cartilage: an infrared fiber optic probe and imaging study. *Appl Spectrosc* [Internet], Apr 30 [cited 2021 Jan 19];58(4): 376–81. Available from: <http://journals.sagepub.com/doi/10.1366/000370204773580194>, 2004.
- [16] A. Hanifi, H. McCarthy, S. Roberts, N. Pleshko, Fourier Transform Infrared Imaging and Infrared Fiber Optic Probe Spectroscopy Identify Collagen Type in Connective Tissues, *PLoS One* [Internet], 2013. May 22 [cited 2021 Jan 19];8(5). Available from: <https://pubmed.ncbi.nlm.nih.gov/23717662/>.
- [17] K.P.H. Pritzker, S. Gay, S.A. Jimenez, K. Ostergaard, J.-P. Pelletier, P.A. Revell, P. Fomina, B. Mizaikoff, A. Kohler, Preprocessing strategies for sparse infrared and Staging. *Osteoarthr Cartil* [Internet], 2006. Jan 1 [cited 2019 May 21];14(1):13–29. Available from: <https://www.sciencedirect.com/science/article/pii/S1063458405001974>.
- [18] H. Martens, E. Stark, Extended multiplicative signal correction and spectral interference subtraction: new preprocessing methods for near infrared spectroscopy, *J. Pharm. Biomed. Anal.* 9 (8) (1991) 625–635. Jan 1.
- [19] V. Tafintseva, T.A. Lintvedt, J.H. Solheim, B. Zimmermann, H.U. Rehman, V. Virtanen, R. Shaikh, E. Nippolainen, I. Afara, S. Saarakkala, L. Rieppo, P. Krebs, P. Fomina, B. Mizaikoff, A. Kohler, Preprocessing strategies for sparse infrared spectroscopy: a case study on cartilage diagnostics, *Mol* 27 (2022). Page 873 [Internet]. 2022 Jan 27 [cited 2022 Feb 18];27(3):873. Available from: <https://www.mdpi.com/1420-3049/27/3/873/htm>.
- [20] S. Wold, A. Ruhe, H. Wold, W.J. Dunn III, The Collinearity Problem in Linear Regression. The Partial Least Squares (PLS) Approach to Generalized Inverses [Internet], *SIAM J Sci STAT Comput*, 1984 [cited 2021 Dec 8];5(3). Available from: <http://www.siam.org/journals/ojsa.php>.
- [21] I. Karaman, E. Mostafa Qannari, H. Martens, M. Skou Hedemann, Erik Bach Knudsen K, A. Kohler, Comparison of Sparse and Jack-knife partial least squares regression methods for variable selection, *Chemometrics Intelligent Laboratory Systems* 122 (2013) 65–77, <https://doi.org/10.1016/j.chemolab.2012.12.005>.
- [22] K.O. McGraw, S.P. Wong, Forming inferences about some intraclass correlation coefficients, *Psychol Methods* 1 (1) (1996) 30–46.
- [23] J. Oinas, L. Rieppo, M.A.J. Finnilä, M. Valkealahti, P. Lehenkari, S. Saarakkala, Imaging of osteoarthritic human articular cartilage using Fourier transform infrared microspectroscopy combined with multivariate and univariate analysis, *Sci Rep* [Internet] 6 (1) (2016) 1–10.
- [24] J. Yin, Y. Xia, M. Lu, Concentration profiles of collagen and proteoglycan in articular cartilage by Fourier transform infrared imaging and principal component regression, *Spectrochim. Acta Part A Mol Biomol Spectrosc.* 88 (2012) 90–96. Mar.
- [25] A.C.S. Talari, M.A.G. Martinez, Z. Movasaghi, S. Rehman, I.U. Rehman, Advances in Fourier transform infrared (FTIR) spectroscopy of biological tissues, *Appl Spectrosc Rev* [Internet] May 28 [cited 2019 Oct 4];52(5):456–506. Available from: <https://www.tandfonline.com/doi/full/10.1080/05704928.2016.1230863>, 2017.
- [26] A. Kohler, N. Kristian Afseth, H. Martens, *Chemometrics in biospectroscopy*, in: *Handbook of Vibrational Spectroscopy*, John Wiley & Sons, Ltd, 2010.
- [27] L.C. Lee, C.Y. Liong, A.A. Jemain, Partial least squares-discriminant analysis (PLS-DA) for classification of high-dimensional (HD) data: A Review of Contemporary Practice Strategies and Knowledge Gaps, vol. 143, *Analyst. Royal Society of Chemistry*, 2018, pp. 3526–3539.
- [28] V. Tafintseva, E. Vigneau, V. Shapaval, V. Cariou, E.M. Qannari, A. Kohler, Hierarchical classification of microorganisms based on high-dimensional phenotypic data, *J. Biophot.* 11 (3) (2018 Mar 1).
- [29] Y.Y. Wang, J.Q. Li, H.G. Liu, Y.Z. Wang, Attenuated total reflection-Fourier transform infrared spectroscopy (ATR-FTIR) combined with chemometrics methods for the classification of Lingzhi species, *Molecules* 24 (12) (2019 Jun 13).
- [30] T.M. Quinn, E.B. Hunziker, H.J. Häuselmann, Variation of cell and matrix morphologies in articular cartilage among locations in the adult human knee, *Osteoarthr Cartil* 13 (8) (2005) 672–678.
- [31] D. Dwyer, C.R. Martin, R. Kendra, C. Sermer, J. Chahal, D. Ogilvie-Harris, D. Whelan, L. Murnaghan, A. Nauth, J. Theodoropoulos, Reliability and Validity of the Arthroscopic International Cartilage Repair Society Classification System: Correlation with Histological Assessment of Depth. *Arthrosc - J Arthrosc Relat Surg* [Internet], 2017. Jun 1 [cited 2021 Apr 7];33(6):1219–24. Available from: <https://pubmed.ncbi.nlm.nih.gov/28162918/>.