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Tissue Characterization by Robotic Palpation with Needle Compression-OCE

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Abstract

Elastography aids in the qualitative differentiation of tissue, be it for organs or tumors. However, less research was conducted at finding methods to accurately measure *quantitative* elasticity, namely the *Young's modulus* E : In this work, we researched the question whether one can derive this modulus from a linear regression between a) a reference measure E from a Hertzian contact experiment, and b) a custom *pseudo-stiffness* $\hat{E}$ specific to our custom indenter - a slightly compressible needle with an embedded optical coherence elastography fiber to measure both the force at its tip and the local strain in a test object. For the experiments, we used a robotic arm actuation to palpate phantoms out of plastirol or gelatine, and heterogeneous animal organs from chicken or lamb in a highly controlled quasi-static compression.

As expected, qualitative differentiation was fairly possible in the form of multidimensional *elastograms*. Quantitative identification of the modulus lacked significant accuracy at values greater than 50 kPa and very soft organs prone to rupture. We refer to more research into special needle designs, non-linear models and strain visibility.

Keywords: elastogram, quantitative elastography, optical coherence, Young's modulus, robotic needle palpation, cancer detection, strain estimation

1 Introduction

If a tumor is stiffer than its surrounding, which is often the case, we can use that difference to our advantage and try to detect it. What we actually do, is to rely on a characteristic biomechanical response: The tumor resists against its deformation by trying to return to its original shape, and it resists more than its surrounding. In other words, it is more *elastic* than the healthy organ. To make it then easier to be localized by us, we may visualize these different responses in a spatial representation, or an *elastogram*. This technique is also called elasticity imaging or *elastography*. To do this, there has been and still are different imaging techniques, which complement each other:

First we have magnetic resonance imaging (MRI), which has a resolution around ca. 1 mm and an imaging depth between ca. 1-1000 mm. Then we have the ultrasound technique (US), which has a resolution around ca. 100 μm and an imaging depth between 1-10 cm. The third technique, *optical coherence tomography* (OCT), fills a smaller niche with a resolution between ca. 10-1000 μm and an imaging depth between ca. 10-100 μm . Therefore, OCT already allows imaging on microscopic level. On that scale, it is superior to the other techniques. But imaging by itself is not enough to show elasticity. We also need to create a situation where the tumor shows a certain resistance: By a slowly increasing, but actively deforming force from outside, we create a *quasi-static* compression on the tumor, which itself shows resistance in form of slowly emerging *visible strain*. We now call the visualisation of those strains *elastography*. In our case, we want to visualize them on a microscopic level and therefore use OCT, which results to a cutting-edge technique called *optical coherence elastography* (OCE). It provides us images with higher spatial and temporal resolution of the strained microstructures, also called *microstrains*. If induced by compression, as we mentioned, we can also call this technique *compression-OCE* (C-OCE).

For the compression, we usually use indenters with a wide and flat surface for the contact with the tumor object (or any arbitrary tissue or material): They cover a large area to create a predictable and uniform force distribution (*stress*) on and in the object, which we often see performed under bench-top systems. However, we are seldom able to see all the strains throughout the whole object under test. In reality, we always depend on the limited visibility inside, which itself as an optical feature is dependent on enough reflection from *backscatterers*. Therefore, in our limited case, we can only measure what we see - a locally restricted strain, which is actually enough: Kennedy et al. discovered in 2012 [4, 21] that for determining the elasticity attribute, we only need a uniform stress, which we ensure with a classical flat indenter, and these *local strains*. With both factors, we obtain what is called the (local) *Young's modulus* E (E-mod), essentially the "resistance-against-deformation", what is simply the proportion between stress σ and (local) strain ϵ :

$$E = \frac{\sigma}{\epsilon} \tag{1.1}$$

A new challenge arises now if we do not use classical indenters: What happens with the

uniformity of stress, if we use, for example, a needle to compress? Because of the tip, a needle invokes compressive force on a very small area, and "pulls" surrounding material in a non-uniform way other than compression, for example by traction. We cannot simply predict the spatial force distribution anymore: The Young's modulus cannot be derived like we used to. But the use of needles has clearly its advantages: They are more fitting in a clinical-medical context, they are non- or minimal-invasive, and they allow even deeper imaging by penetrating the tissue surface. In previous works [8], we also discovered that by measuring the force strictly at the needle tip, we can at least ensure a uniform force. This allowed deep elasticity applications based on a surrogate measure $\hat{E} = F_{tip}/\epsilon \neq E$. Because of a new needle design, which consisted of two OCT fibers, an integrated epoxy-compression layer and a beveled tip, we were able to measure force on the needle tip and strain at a greater depth. Earlier designs by Qiu et al. had single fibers and compressible Fabry-Perot cavity layers instead [10].

However in this work, we propose a metallic needle which is slightly compressible in itself. Further we also use a single OCT fiber, whose signal contributes to both the measure of the force-at-tip and the local strain in a test object - again for an elasticity surrogate value $\hat{E}$, which we from here on call the *pseudo-stiffness*. In a new step, we then try to infer a linear relationship between $\hat{E}$ and the supposed E , which we measure separately with a spherical indenter. Additionally, for the compression to be both highly flexible and controlled, we use a robotic arm for the needle actuation. We also try to apply this new OCE technique to various local points of different heterogeneous organs to generate elastograms of cumulated elasticity. In the end, we not only evaluate their qualitative suitability for tumor segmentation, but also hopefully can attest quantitative accuracy to some extent.

1.1 Background

1.1.1 Elasticity

As mentioned, elastography uses the measure of elasticity in a material to visualize the difference or amount of resistance to its deformation. If the force is taken away, elasticity ensures that it returns to its original shape. If it does not, we call that *plasticity*: The ability to remain deformed. We simplify the elastic properties and their models by assuming linearity, that means proportionality between the deformation and the underlying force. This then applies not only in the vicinity of zero stress and strain, but throughout the motion (Hooke's law). We call this *linear elasticity*. This assumption applies in all directions with the same magnitude (isotropy) and independent of time, i.e. changes in deformation occur without delay (non-viscoelasticity). We also assume that the material is uniaxially restricted by a rigid ground, but otherwise expands without restriction.

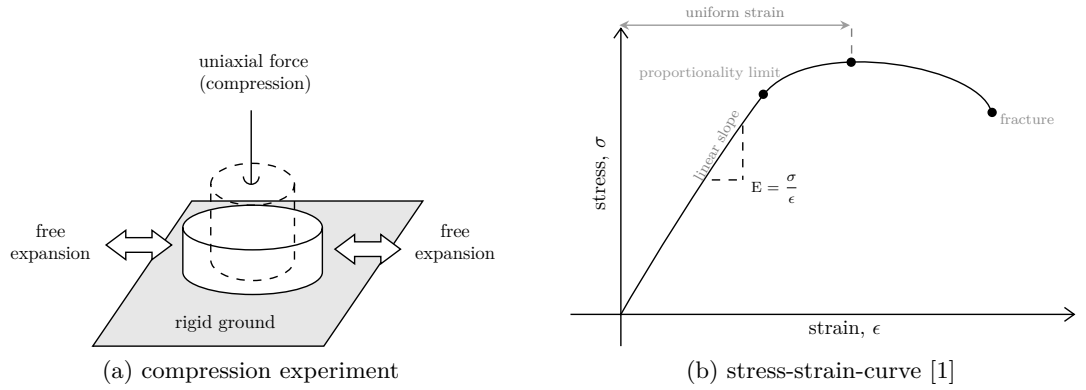


Fig. 1.1: A typical setup of a compression experiment is shown left (a). Key environmental factors are a compressing force acting only in a single direction (here from above) and a ground which retains the test object in only that direction (leaving space for free lateral expansion). An elastic test object returns to its original shape "like a rubber ball", if we remove the mentioned compressing force. To the right (b), we can see a typical stress-strain-curve, which is a simple graph of its elastic reaction (strain) to compression (stress). Importantly, the reaction is segmented into parts with distinct behaviour, defined by its curve *slope*. The linear slope under the proportionality limit is our target property, the *Young's modulus* E .

Especially in biological tissue, the elasticity of a material behaves characteristically [22] and can be used for diagnosis [6, 21]. At the cellular level, the extracellular matrix (ECM) with its elastin protein ensures integrity and recoil after stretching, contracting, pinching, or poking [17]. If we restrict those deformations to a single axis, namely uniaxial extension or compression, we can quantify its elasticity by stress $\sigma = F/A$, i.e. by the force F (in N) per impacted area A (in m^2), and the resulting *relative* deformation (strain, in %). Both factors are proportional in the initial part of their *stress-strain-curve* [1]. Its tangent slope under its proportionality limit is then our wanted Young's modulus [20]. (Other moduli measure the slope in bulk or shear motions.)

By mapping the measured elasticity values over a defined area, we attempt to differentiate between tissues: The underlying pathological states alter the elastic property [21] especially in cancer. Moreover, more accurate and precise methods for elasticity quantification may allow for better explicable identification and therefore the diagnosis of pathologies, e.g. cancer in the breast, thyroid or prostate [14], or diseases in the liver [18]. At least, elastography may assist clinical staff with additional information about the size, shape and location of irregular tissue formations by determining elasticity boundaries in gradually deeper axial layers [5] or across the surface to produce a morphological segmentation.

1.1.2 Palpation

A physician's method for determining elasticity consists of acting on the target tissue or shaped organ with his own hands and fingers, stabilizing it and feeling the deformation and force. This manual method is restricted in the accessible area and depth. It is also distorted by adjacent tissue due to the natural width of the fingers. It further relies on experience and subjective perception to classify the elasticity of a target [18]. Therefore, this process and the result are relatively biased.

In comparison, a robotic-actuated indentation process is programmable, more accurate and more precise. As the end-effector, the area of the indentation is interchangeable. Examples include wide cylinders, spherical balls or needles, all of which are usually rigid.

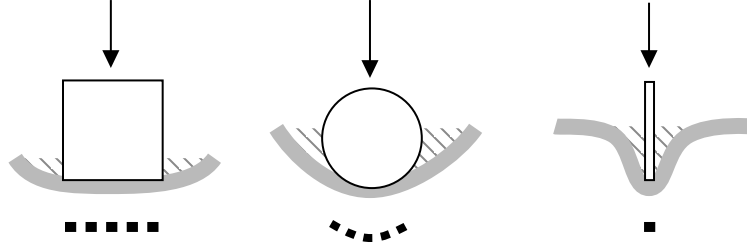


Fig. 1.2: We show a diagram of three different indenter shapes during indentation of an elastic surface. From left to right: A flat indenter with a large uniform contact, a spherical indenter with some uniform contact and a needle indenter with a non-uniform contact. As the contact area shrinks (black dots), the force is less evenly distributed: More inter-tissue "pull" occurs, force is more concentrated. The probability for rupture increases and assumptions of linearity become more and more unrealistic.

For cylinders or similar, a flat indentation surface covering a larger part of the test object means that the area of applied stress is more uniform in relation to the strain: The Young's Modulus E results in principle from measuring the acting axial stress component σ with known uniform contact area

$$\sigma = \frac{force_{axial}}{area_{contact}} = \frac{F}{A} \quad (1.2)$$

and the resulting axial strain component ϵ as a spatial x derivative estimation of the axial displacement u , [21],

$$\epsilon = \frac{\delta u}{\delta x} \approx \frac{\Delta displacement_{axial}}{length_{axial}} = \frac{\Delta L}{L_0} \quad (1.3)$$

for

$$E = \frac{\sigma}{\epsilon} = \frac{F * L_0}{A * \Delta L}. \quad (1.4)$$

The size of the indentation then only hinders targeted elasticity measurements. Depending on the circumference, spherical ball indenters allow more flexible and spatially resolved measurements, which are more similar to a manual palpation. Under classical contact mechanics, and with a ball indenter of known dimensions, we can estimate the Young's Modulus: E.g. by curve-fitting to the measured values of merely force and distance [3]. But needles are different: In a clinical context, they enable non-invasive, minimal-invasive or even deep tissue measurements [9] similar to penetrating biopsy needles. However, tissue rupture caused during the indentation complicates the assumptions we make for the elasticity model. Even with a surficial needle indentation, where the contact area evolves into a dynamically changing area A_{dyn} , the acting stress σ quickly degenerates into non-linearity and the computation of the modulus becomes more difficult:

$$E(A_{dyn}) = \frac{F/A_{dyn}}{\epsilon} \quad (1.5)$$

With the area factor A falling out of the linearity assumption, we still try to ensure a uniform increase of the force up to a specific maximum at the *tip* in order to determine a proportional pseudo-stiffness $\hat{E}$ [8], which can then disregard the contact area:

$$\hat{E} \approx \frac{F_{tip}}{\epsilon} \quad (1.6)$$

But this result is highly specific to the properties of the needle and clearly does not equal E . However, it is a meaningful surrogate [8]. We later try to relate resulting $\hat{E}$ to a corresponding E in order to quantify the elasticity in an indirect way.

1.1.3 OCT

To estimate the relative strain ϵ induced by the indenter, we now use OCE: It visualizes the stepwise convergence of the indenter front and the reflecting tissue during contact. We apply this not only to the test object, but also to the internal deformation of our near-rigid needle itself to measure the acting force-at-tip [10].

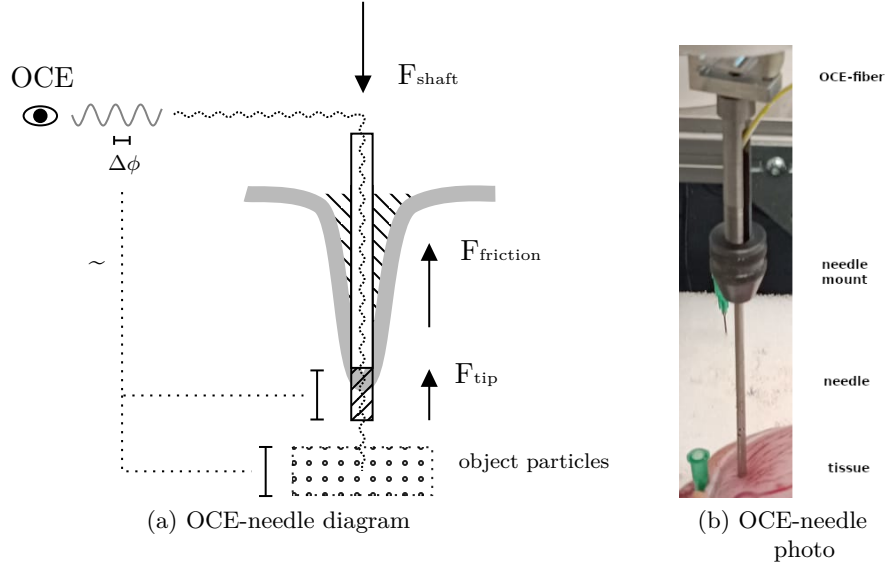


Fig. 1.3: On the left side (a) is a diagram of a needle with an integrated OCE fiber during indentation of tissue. Three black arrows represent the forces which are involved: The compressing force F_{shaft} at the needle shaft, the resisting force F_{tip} at the needle tip and the frictional force $F_{friction}$ at the needle sheath. With the signal from the fiber, we can additionally measure F_{tip} and object strain: Displaced reflections from inside the needle tip and object particles are represented in a shift $\Delta\phi$ of wave phase - which are made visible by the OCT device. On the right side (b) is a photo of such a needle during indentation.

This avoids the measure of additional forces that do not act directly on the tip, especially at the level of deeper tissue: E.g. frictional forces that a conventional (piezoelectric) force sensor attached to the shaft cannot avoid to measure [8]. However, the accuracy of the measured values is subject to additional limitations. A reasonable force resolution depends on the degree of axial flexibility of the indenter and the resolution of the underlying OCT signal. In our case of a metallic needle, we embed an OCT fiber inside, whose OCT light shone in the axial direction through a integrated semi-reflective medium, and only then into the test object. Compressibility of the needle was prepared by making small perforations into the needle sheath. Such a modification varies the possible reflection distance of the OCT light in comparison to an external reference reflection of the same OCT source. This results in a certain wave interference pattern, which provides relevant image information at certain axial distances.

But in contrast to sample-wide global strains, we can only measure visible strain: Those are displacements of the object particles reached by the limited range of the OCT light. Therefore we can only cover local strains. To make them visible, an interferometer measures the reflected interference, which itself is generated by several light waves from the same light source and bandwidth within a short coherence distance. This also consequently influences the imaging depth of the OCT device. Depending on their differences in optical path length, the superimposed waves add up to destructive or constructive elevations (also called fringes) in the resulting interferogram. However, instead of taking the difference in wave amplitude, which is fairly known to the human eye as the intensity contrast, the other wide-spread imaging approach is to take the

change and direction of the wave *phase* to estimate the different propagation distances. Those phase or distance changes are either produced by a change of refractive index, or, more importantly to our cause, by deformation.

This transformation chain of "phase-to-distance-to-shape" at a given reference distance is more robust to environmental influences in a double-path interferogram, where the source light is first split with an external beam splitter and then recombined after traveling two different paths. When used in a Michelson-interferometer with a light source of narrow bandwidth, this specific referenced distance is modulated by a moving mirror that generates the time-delayed wave coherence for the interference in a *time-domain* OCT (TD-OCT):

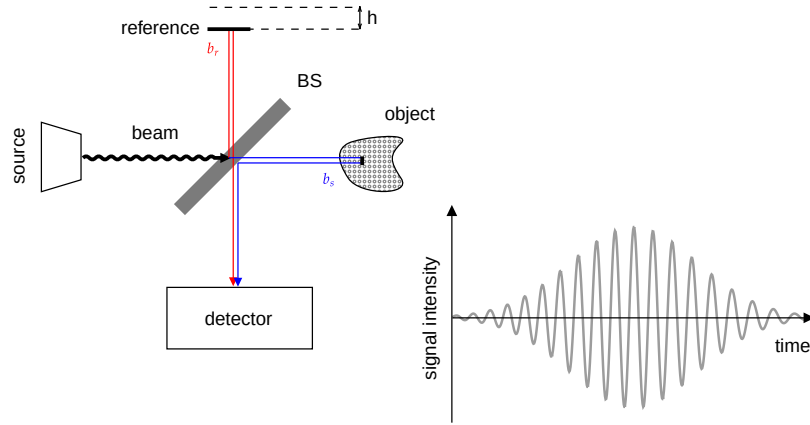


Fig. 1.4: A diagram of the mechanism in a Michelson-interferometer: We see a source sending a beam of short-coherent light through a beam splitter (BS), where it is split into a reference beam b_r (red) and a sampling beam b_s (blue). They both now travel different paths, where they either being reflected by a reference mirror or by a sample object. Finally merged at a detector, their interference pattern is analyzed for differences in signal frequency, strength and phase between those reflections, which creates a *cross-section image*. By modulating the distance h of the reference mirror, we can also change the imaging depth inside the object [12].

From their interference we obtain a spectrogram, which represents the computed density of frequencies sampled at certain times. Based on those frequencies, it is then possible to extract the reflection intensity and phase at varying distances. This finally leads to our time-series of 1-dimensional amplitude scans (A-scans).

Another variant to the interferometer is the *swept-source* OCT (SS-OCT): The distance modulation is here achieved by tuning the wavelength of a laser light. However, we only use a third variant: A spectral-domain interferometer in a *spectral-domain* OCT (SD-OCT, also known as frequency-domain OCT or FD-OCT). It captures the length-resolved spectrum of a broadband light, which allows sufficient interference without modulation - in other words, simultaneously in a single exposure [19].

In short, SD-OCT enables cross-sectional, microscopic and high-resolution axial images transformed from spectrograms of propagated white light. Those reflection scans at

1 Introduction

different distances or depths correlate with their multiple wavelengths and produce typical amassed blinking dots of data, so-called "speckles". Although they are susceptible to noise, hardware-specific adjustments such as a sample rate increase or software-based denoising quickly leads to a distinct contrast in intensity and phase data.

With some theoretical background on elasticity, palpation and OCT raised, we now move on to the methods and material of our work.

2 Methods and material

As we know, for the detection of elasticity, we first needed to induce stress in the object. For that we decided on robotic actuation.

2.1 Actuation

The actuated force to the object happened in the form of an indentation along a single distinct axis. Simultaneously, we measured the deformation over time and distance. We refer to this process as the actual *robotic palpation*. The test object itself was supported, leveled and fixated by a styrofoam ground, which not only served as a raised and rigid surface, but was still penetrable by the needle as a safety caution for our tools.

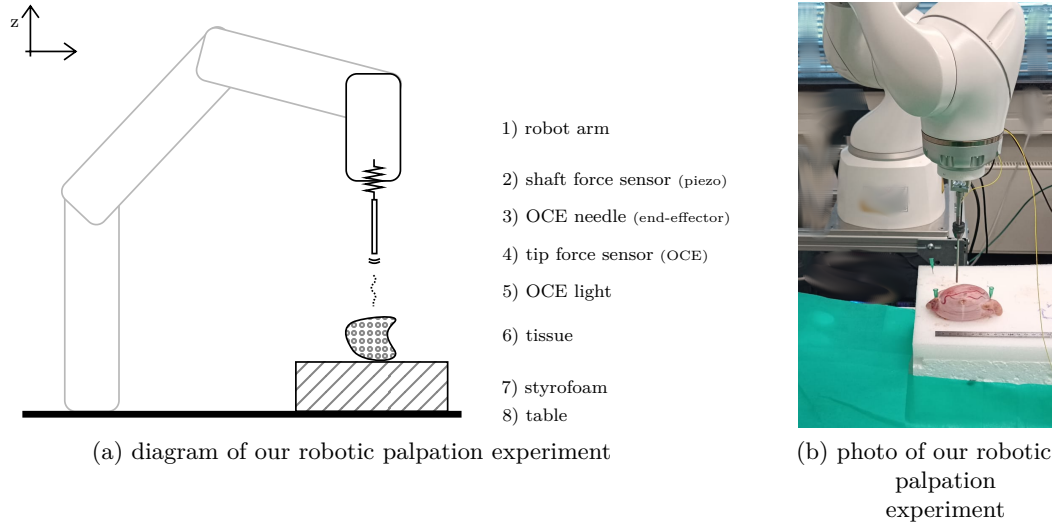


Fig. 2.1: On the left side is a diagram (a) for the setup of our robotic needle palpation experiment. Depicted are the robot arm (1), which is responsible for the actuation, the piezo-electric shaft force sensor (2) for measuring the total uniaxial force, the OCE-needle indenter (3), which induces tissue stress by compression, an integrated force sensor (4) for measuring the different tip force, the OCE light (5), which shows the displacement of reflected backscatterers, the sample tissue itself (6), which exhibits measurable strain, the styrofoam ground (7) for stability and finally a table (8) for some leverage. On the right side is an actual photo (b) of that setup inside our laboratory at MTEC.

The actuation in three dimensions was automated by a KUKATM IIWA 14 robotic arm, which was suitable for research [15] and also served as the measuring device for our spatial actuation data: Metric coordinates in its Cartesian system were logged throughout the palpation. The planning of the end-effector's trajectories was commanded in the

form of joint angles through its inherent *Fast Research Interface* (FRI) [13], which itself was accessed by our own connection layer that we programmed in accordance to that interface and within the *Robotic Operating System* (ROS) framework [11]. It encapsulated sequential robot arm actuation and reaction commands by abstracting them into messages of a topic-based publish-subscribe system. Additionally, we installed the *MoveIt*-library [2] of the ROS ecosystem to facilitate the planning and execution of trajectories.

The actuation planning of the robot trajectory was manually specified by static parameters and automatically controlled by dynamic parameters: The static parameters included multiple depth-resolved layers of grid points (with the deepest layer being closest to the styrofoam ground):

1. *Target points* at maximal actuation depth without contacting the styrofoam,
2. *hover points* at a fixed distance to the target points and at a certain distance to the object surface, and
3. *palpate points* in-between the target layer and the hover layer. They represented all linear trajectory points the end-effector and consequently the indenter were supposed to follow.

For each trajectory, there were velocity factors to control the speed at which the actuation was performed. The dynamic parameters included streamed data of a ME-Meßsysteme™ KD24s tensile force sensor [7], which was attached to the indenter shaft for the synchronous monitoring of the *force-at-shaft*. That sensor was also used as reference for our linear calibration between the compression of the needle and the perceived force-at-shaft - the foundation for our force-at-tip estimation. As a remark, the compression was made visible by OCE and therefore processed a-posteriori due to the larger computational load. Force-at-tip estimation was therefore asynchronous compared to the data of the shaft sensor. For each palpation, there were two additional and important static parameters, the minimum and maximum force to that shaft sensor, which controlled the force interval where our palpation payload was recorded to disk: At the minimum force, the point of the trajectory where the end-effector reached by then was declared the *contact point*, a spatio-temporal point that represented the first local contact of the indenter with the surface of the object. It was also typically around that point where larger deformation of the object took place - it would prove crucial to record that timespan. Going further in the sequence, we would reach the point of the trajectory at the maximum defined force, the *retract point*: It marked the start of the return motion of the indenter back to its original position.

2.1.1 Actuation stages

The actuation of the end-effector basically took place in five chronological stages, every-time for each target point: Hovering, contacting, relaxing, palpating and retracting.

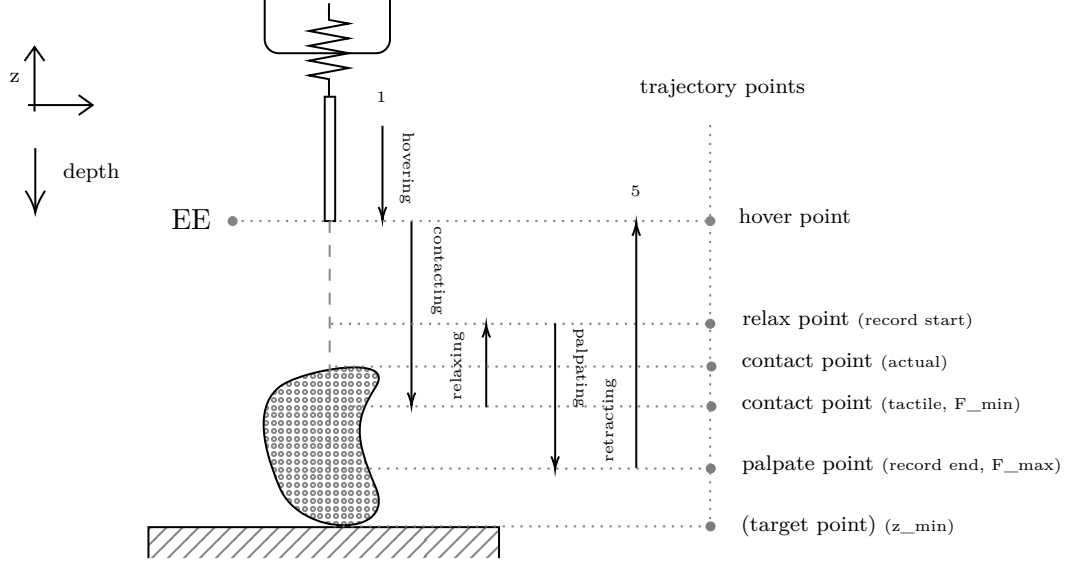


Fig. 2.2: Depicted is a diagram of our programmed actuation stages of a *single* palpation. An experiment can contain multiple palpations, but each palpation goes through the same five stages shown as small vertical arrows. The end-effector (EE) follows a set of trajectory points, which themselves contain the different points of interest (right side) - reached at the different stages. Those points represent crucial triggers or transitions of certain functionalities (in brackets). In total, they are responsible for a successful experiment run.

As the name suggests, in the first stage, the indenter was located at a fixed z -coordinate (*hovering stage*): That position was at a certain distance (height) from the object surface and the target point. In the second stage, the indenter was moved in a linear motion towards the target point to find the tactile contact point with the lowest force (*contacting stage*). The accuracy of this search depends on the resolution of the shaft force sensor, the approaching velocity and the stopping time delay of the actuation. There was the chance that the indenter may have already entered the object considerably and the actual contact point would have been overshoot and not recorded in time. The third stage compensates for this "delay" by moving the trajectory back by a certain distance (*relaxing stage*). The recording process then began. Both force sensors and the OCT signal then should have included the actual contact in the next stage (*palpating stage*): The indenter re-entered the test object until it reached the retract point at a defined maximum force and the recording stopped. The actuation then entered the fifth stage, in which the indenter was retracted along its entering trajectory path to exit the object until it reached the initial hover point again (*retracting stage*). The actuation then moved to the next target point and the sequence was repeated. Each record was supplemented by auxiliary data such as time (in ms), Cartesian position (in m) and axial shaft force (in N).

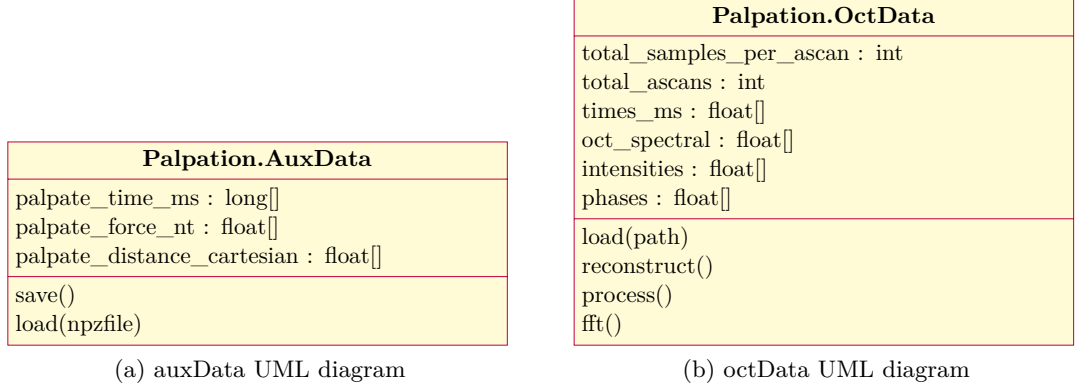


Fig. 2.3: We present the recorded data objects as UML class diagrams. For each palpation, we obtained data encapsulated in either *auxData* (a), or *octData* (b). The *auxData* contained the sampled UNIX timestamps (in ms), forces from the shaft force sensor (in N) and the cartesian distance traveled on the z-axis (in m). We only implemented the methods for saving and loading to serialized npz-files. The *OctData* on the other hand, contained the number of total pixels which are sampled per A-scan, the total number of A-scans per OCT record, the timestamps from the OCT device (in ms), the actual OCT spectral data and their intensities and phases after a fast-fourier-transform (fft). We also implemented methods for loading, reconstruction and post-processing of the image data.

2.2 Indenters

As indicated, we chose both a needle and a ball as the indenters for our experiments. The latter spherical indenter produced no OCT records, because it only served as references for our regression between OCT-resolved pseudo-stiffnesses $\hat{E}_i$ and those Young's moduli E_i , which we also just called the "second calibration". For a certain force-distance-curve of a palpation i , which was recorded and time-aligned from the auxiliary data, we took the known Hertzian contact model between a rigid sphere and an elastic half-space,

$$F = \frac{4}{3} * \frac{E}{1 - \nu^2} * R^{\frac{1}{2}} * d^{\frac{3}{2}} \quad (2.1)$$

with force F , distance d , a poisson ratio $\nu = 0.5$ and a indenter radius $R = 0.022$. This model then produced our reference modulus E [3].

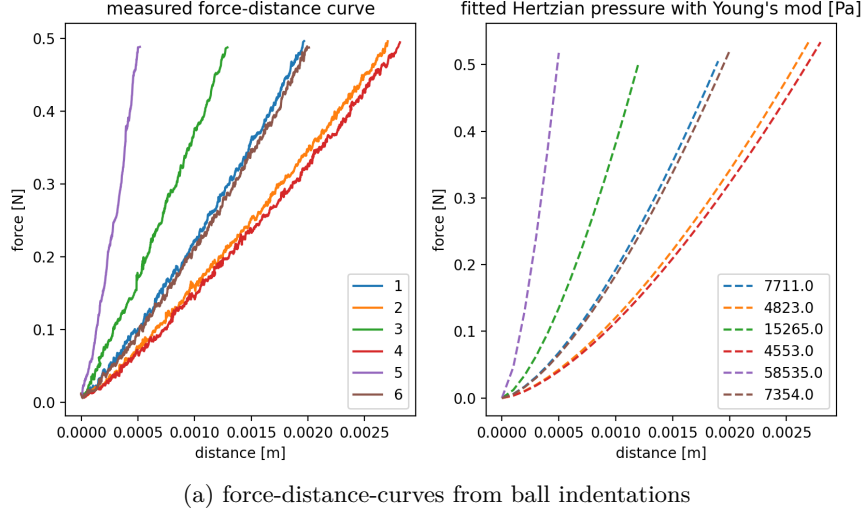


Fig. 2.4: On the left side (a), we show a diagram of different force-distance curves (colored), which we recorded from ball indentations of our six different plastisol phantoms. To determine their elasticities in the form of Young's moduli, we then fitted Hertzian model curves to them: The middle side (a) presents them with dashed lines (same colored). On its legend, we can see the resulting elasticity values. On the right side (b), we took a small photo of our ball indenter.

Coming to the visual strain estimation, we then took the other indenter: A flat-tipped metallic needle made slightly compressible by multiple small perforations - these did not hinder the stability of the needle, nevertheless. An embedded OCT fiber sequentially observed through air, fixed glass, and towards the external object. That fiber was basically responsible for all of our OCT data.

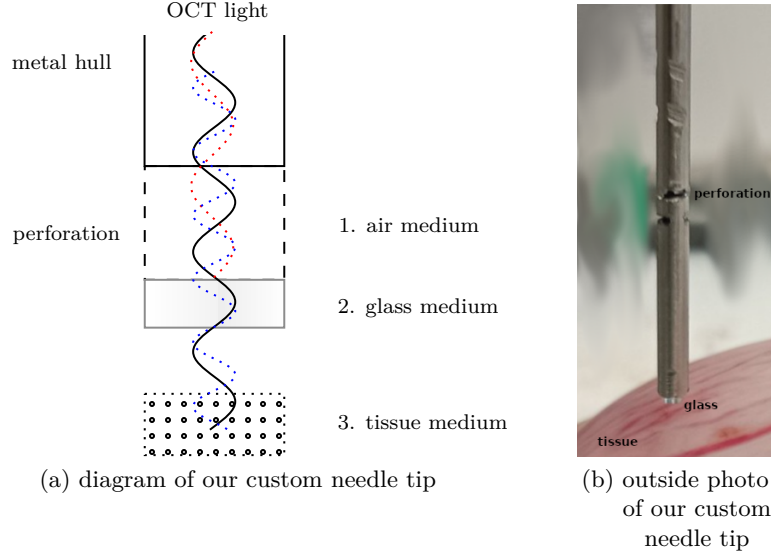


Fig. 2.5: To the left (a), we depict the inside design of our needle tip: The OCT light beam gets propagated first through air, glass and then into a sample tissue. Major reflection occurred twice: Once at the glass entry (red dotted), and once inside the tissue (blue dotted). At indentation, enough force was responsible for the perforated part to compress. By that, the propagation and the reflection distance changed. These small changes were measurable by our OCT detector. The change of the first reflection was ideally proportional to the force and therefore produced an estimate of that force. The change of the second reflection were simultaneously the displacements of backscatterers, by which we then derived our object strain. To the right (b), we show the photo of the actual needle tip and its perforations.

2.2.1 OCT data

The OCT base device was a ThorlabsTM TELESTO SD-OCT imaging system [16] with a superluminescent diode light source of 1325 nm centre wavelength, 160 nm bandwidth and a linear indium-gallium-arsenide array-based spectrometer. It provided up to 7.5 μm depth resolution in air, 512 px per A-scan, a 2.5 mm imaging depth in the air and up to a 96 kHz sampling frequency of continuously received interference spectra [16]. In our case, we found it sufficient to set the sampling frequency down to 5.5 kHz for smaller data records and a faster data processing. The raw spectrograms were coded in unsigned 16-bit integers as density-colored pixels per frequency (x-axis) over scans in time (y-axis). The pre-processing of the spectrogram included in true order the dechirping, offset removal, DC subtraction and linear-/logarithmic scaling of the frequency density data. Then, we horizontally applied the fast Fourier transform over time to obtain the amplitude and phase of the different frequencies for a 2-dimensional image of successive amplitude scans (A-scans): They represent the reflection intensity at a certain depth (y-axis) over time. However for the displacement analysis, we further took the phase images at each scan for a phase-resolved local strain estimation. In preparation, phase-image preprocessing included in true order the clipping to relevant depth- and time-intervals, unwrapping,

denoising and normalizing.

2.2.2 Spatial multiplex

Since force-displacement and strain-displacement shared the same OCT signal and were only multiplexed in depth, both were presented on the same phase image and needed to be processed separately: We assigned specific depth-intervals to the force estimation and the strain estimation respectively. Because of the limited compressibility and the position of the outside reference mirror, the internal displacement of the glass layer *towards* the OCT fiber output was of a lower magnitude and of a different sign than its strain counterpart. As we took that into account, its depth-interval ranged only over a small number of successive pixels (< 30 px at maximal 0.5 N) per A-scan. We separated them by its lower and inverted phase-shift over time. The signal strength especially was stronger at compression, but also at distances of overlap between internal and external reflection: Although we configured the distance by their shared reference, we could not successfully overcome artifacts and misestimates of the spatial multiplexing. Both information were sometimes just inevitably entangled and lost. However, due to the shorter reflection distance and the unobstructed propagation in air, the information about the internal compression was considerably stronger. Here, signal strength formed to an extent the z-order by which they were demultiplexible.

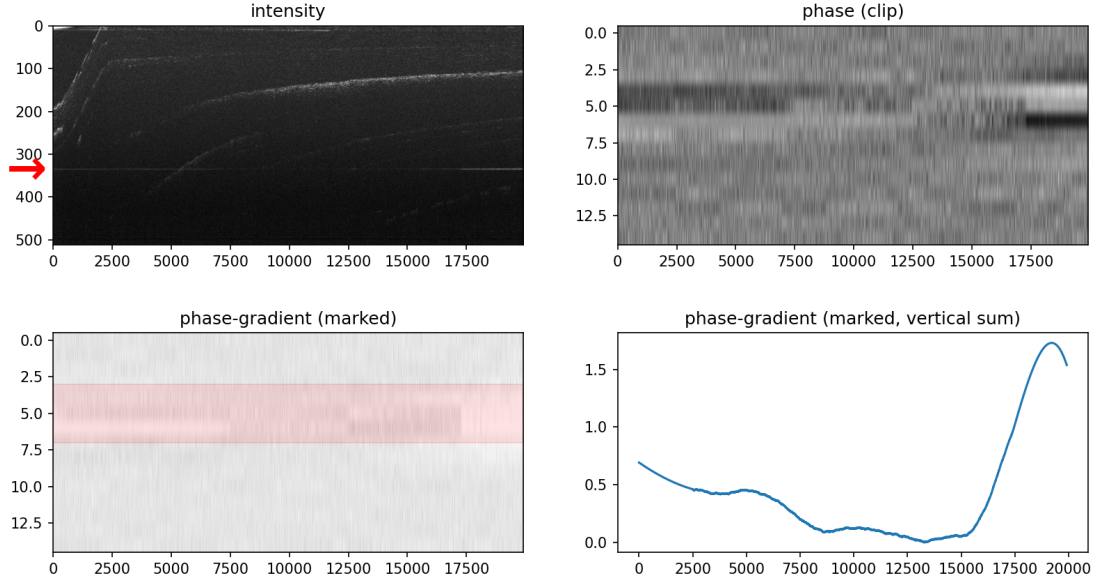


Fig. 2.6: A spatial demultiplexing of our OCT signal, shown on four graphs: At the top left, we see the original intensity image as a quick preview to our reflection data. On the y-axis we can see the imaging depth z in pixels and on the x-axis the A-scan indices, which correspond to a time t . At ca. 330 px depth, a red arrow depicts the reflection of the glass layer, whose phase-change over time has to be extracted. At the top right, we see a clip of the phases, zoomed in to that depth. The contrast between the phases shows the separable signal. At the bottom left, the pixel rows were automatically selected by the difference to the mean gradient: $\delta\bar{\phi}_{row} > \delta\bar{\phi}$. In other words, the mean phases in the wanted rows changed more than the mean phase in its background. At the bottom right, we see the vertical sums of those extracted phase-changes throughout the scans t , which were then related to our force-at-tip.

The phase-shift of the extracted internal compression now served as the first cornerstone in our elasticity estimation. However, would it be only for qualitative comparisons, the need for force and stress estimations could have been avoided if we ensured a uniform stress [4] throughout the compression and over the tested objects. Since we again could not guarantee that, e.g. the same stress on one object may lead to rupture in another, we were required to measure the force at the needle tip. That force-at-tip sensor was essentially dependent on its resistance to deformation and was recorded from displacements in the internal glass layer. Since we presumed a specific refractive index, we were then able to convert the phase change to its respective displacement and model it to a respective force-at-shaft in a *displacement-to-force* calibration, which we also simply named the "first calibration". In other words, we searched for a coefficient a_F from

$$F_{tip}(t) = a_F * \sum_{z=i}^{D_{glass}} \delta u_{glass}(z, t) = a_F * \sum_{z=i}^{D_{glass}} \frac{\delta\phi(z, t) * \lambda_0}{4\pi n_{glass}} \quad (2.2)$$

with the glass displacement gradient δu_{glass} at time t and depth z , which itself is converted from the phase gradient $\delta\phi$ at same time and depth, refractive index n and

center wavelength λ_0 . Notice that we took the sum of displacement changes over the total glass layer depth D_{glass} .

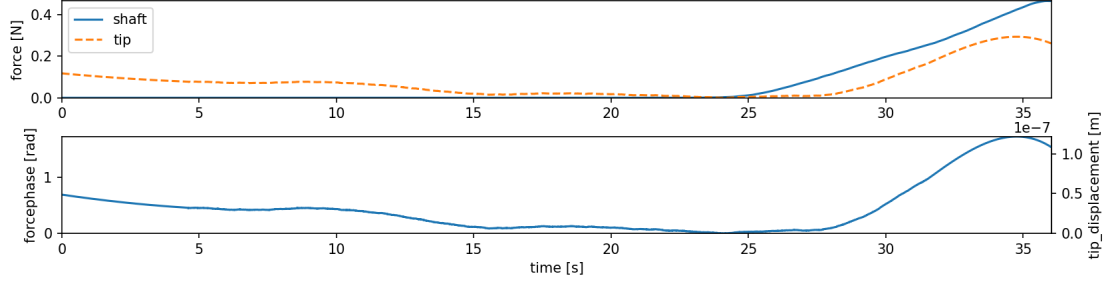


Fig. 2.7: Two diagrams show the linear regression between the force measured at the shaft (top, blue line) and the phase gradient of the glass reflection inside the needle (bottom). The dashed orange line shows the converted force, which is estimated at the tip. We can see a slight increase of the phase gradient at the beginning where some overlap between the tissue reflection and the glass reflection occurred. This led to an initial overestimate of the force-at-tip.

From different phantom palpations, where we assumed both forces to be most reliable throughout the compression, we then obtained a mean $\bar{a}_F$ specific to our needle: Our force-at-tip sensor was ready to use.

2.3 Local strain

After the force component, what we were then essentially trying to do, was to count strains and see how much strain equalled certain E-moduli. Since strain is only produced by a particle displacement *relative* to another particle (in other words, a local position changes *differently* to another local position), strain is basically a measure of *difference*.

One method to measure that difference is to find a visible particle (backscatterer) in an object and see its position change by the phase-shift of its reflection. We then compared this phase-shift to the phase-shift of another visible particle by a simple subtraction, or *finite difference* (FD). Divided by their spatial distance, we would obtain the local strain. This difference quotient between the changes in displacement and depth was possible to be extracted exclusively within a single A-scan, which resulted in depth-resolved *inter-scan* strains. Depending on the opacity and reflectivity of the object's material, the signal was subject to more random noise and consequently inhibited a lower signal-to-noise-ratio (SNR) through depth. This meant for greater depths that we could not see all displacements by its phase-shift and the relative strain was overestimated.

Otherwise, image filters compensated for speckle noise and improved significantly on the payload signal. This was especially noticeable in the strain data since it had to travel further. However, the raw force-at-tip data also exhibited significant noise without averaging due to the multiplexing. If we then introduced the horizontal time dimension to determine *cross-scan* strains of the full indentation, we could not avoid to also introduce OCT artifacts, signal losses and phase discontinuities with higher probability.

2.3.1 Contact point search

But before we dive further, we need to emphasize that with the introduction of time, we needed to recognize *when* we wanted to count strains: Was it too early, then the rapid approach of the object was miscounted as too much strain, and the elasticity was underestimated. Was it too late, then the short interval contained too little strain, and the elasticity was overestimated - or our conversion model would not inhibit enough breadth.

We also could not avoid to unwrap the phase along the imaging depth: Everytime the phase exceeded 2π , its cyclic nature caused a discontinuity or a "jump". Those phase jumps were also expected along the time axis with increasing indentation distance. However, the unwrapping allowed us to isolate the one A-scan which recorded the contact of the needle with the test object, namely the *visual* contact point before having to rely on the force sensors: Those tactile sensors are delayed by their compressibility. In other words, we had a visual record on the contact first: The change over time of the phases closest to the needle typically reached a maximum by then. In our case, because we adjusted the OCT reference mirror for the depth z on the y-axis to coincide exactly with the outward distance, we were able to select the first 50 pixel rows of the phase image as a window to be observed for the contact. In theory, time-successive and comparable strains were then obtainable from the very start of the indentation until the retraction.

But unfortunately, in practice, the OCT artifacts led to frequent failure of this search, and we had to discard many points found that way. In summary, we had the choice between three start points of the strain analysis:

1. The aforementioned *visual* contact,
2. the tactile contact at the *shaft* and
3. the tactile contact at the *tip*.

But in the end, we could only resort reliably to the tactile contact at the shaft - which led the shortest strain interval.

2.3.2 LS by second-half

We emphasize: Locality of our strains meant for the reference position or distance to not traverse the whole length of the object, but only a limited observable length: In our case, it was limited to the OCT imaging range *and* by the material opacity. With advancing indentation, increasingly more object particles entered this observable range, whose apparent approaching we perceived as a greater phase-shift or displacement in the respective deeper portions of the A-scan. But in reality, the greatest displacements happen closer to the needle tip and we inverted the sign of our finite difference to measure the correct strains. In other words, strain from displacements *towards* the needle was actually *negative* deformation, which led rightfully to *compression*. One way to reference these closing displacements was then to half the imaging range and only compute the difference of the upper half to the lower second half by that distance. Naturally, we would neglect the strains in the second half.

Algorithm 1 LS by second-half: We enter 2-dimensional displacements d and weights w of sizes $D \times T$ (depths x scans) and obtain a 2-dimensional weighted strains s of same size by reference to displacements in the second half.

Input: $d = [D][T]$, $w = [D][T]$

Output: $s = [D][T]$

$j \leftarrow 0$

while $j < T$ **do**

$i \leftarrow 0$

while $i < D/2$ **do**

$s[i][j] \leftarrow d[i][j] - d[i + (D/2)][j]$

▷ subtract by second half

$s[i][j] \leftarrow s[i][j] / (D/2)$

▷ divide by half D

$s[i][j] \leftarrow s[i][j] * w[i][j]$

$i \leftarrow i + 1$

end while

$j \leftarrow j + 1$

end while

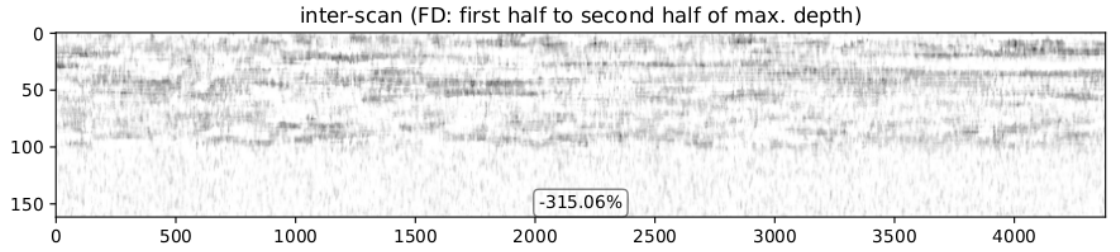


Fig. 2.8: A phase gradient image of the local strain, computed by the *second-half* algorithm. We notice that the depth is halved on the y-axis and most strain is depicted as black pixels, which correspond to the negative strain "upwards" to row zero in a compressive deformation.

2.3.3 LS by first-greatest

Alternatively, we came up with another reference approach. It is based on the idea that only because we did not see a reflection below a certain depth, it did not mean there was no displacement. Certainly, if we moved the needle down, the ground moved closer. This meant, we could extrapolate the greatest visible displacement to particles in the depths below, since the ground "particle" had surely *at least* the same "displacement". To be more precise: First, we only indented in a unidirectional motion and measured in that same direction. Second, only compression was possible, and the object cannot be pushed by or further the ground. Therefore, no involuntary compression or expansion should have happen, and we could extrapolate the deeper, invisible displacements uniformly by the value of the greatest visible displacement. However, the strain estimates from different methods are not interchangeable: They were based on different "localities". As the locality reference to this particular method served the total imaging range D . Naturally, we discarded the smaller displacements below the depth of the greatest displacement (otherwise we would have strains erasing each other) and strains closer to that depth were overestimated.

Algorithm 2 LS by first-greatest: We enter 2-dimensional displacements d and weights w of sizes $D \times T$ (depths x scans) and obtain 2-dimensional weighted strains s of same size by reference to the greatest displacement in the respective scan.

Input: $d = [D][T]$, $w = [D][T]$

Output: $s = [D][T]$

$j \leftarrow 0$

while $j < T$ **do**

$i \leftarrow 0$

while $i < D$ **do**

$s[i][j] \leftarrow d[i][j] - \max(d[:,j])$

 ▷ subtract by greatest in scan

$s[i][j] \leftarrow s[i][j]/D$

 ▷ divide by full D

$s[i][j] \leftarrow s[i][j] * w[i][j]$

$i \leftarrow i + 1$

end while

$j \leftarrow j + 1$

end while

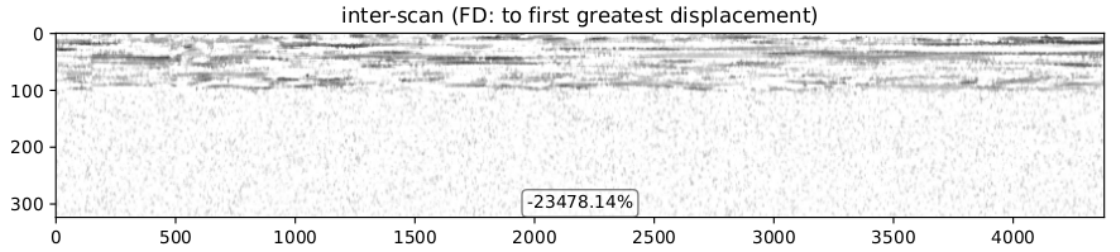


Fig. 2.9: A phase gradient image of the local strain, computed by the *first-greatest* algorithm. It found all the strain which the other algorithms also found, but included in its search also the second half of the imaging depth. With the limited visibility, however, all it found there additionally was noise, which led to a significant overestimation of strain. But since we computed a pseudo-stiffness, the uniform overestimation had no impact on the linear regression of the Young's modulus - the strain estimates were still as functioning. With more visibility, we predict a better performance, nevertheless.

2.3.4 LS by pixel-tracking

The imaging of the indentation process also allowed so-called "pixel-tracking" over time, or specifically along the x-axis of the 2-dimensional image: For each successive A-scan we converted the visible backscatterer displacements in μm , which themselves were converted from phase-shifts, to adjacent pixels on the image where we would find the next phase-shift to convert. In other words, we would start at the leftmost pixel column and "trace" them from scan to scan according to the phase information. Naturally, this method is limited to the pixel resolution of the image and involves rounding to the nearest integer pixel. Additionally, we would "lose sight" below the initial number of tracked pixels because we did not track later-arriving pixels entering the sampled depth, or in-between the pixels because they would diverge or converge (or even merge). Interestingly, this method had a particular advantage: We "lost" sight of significant noise

as well, which would otherwise sum up over time.

Algorithm 3 LS by pixel-tracking: We enter 2-dimensional displacements d and weights w of sizes $D \times T$ (depths x scans) and obtain 2-dimensional weighted strains s of same size by reference to tracked displacements in the second half.

Input: $d = [D][T]$, $w = [D][T]$

Output: $s = [D][T]$

$p \leftarrow \text{array}[D][T]$

▷ array of "moving" pixels

$p[:,0] \leftarrow (0, \dots, D)$

▷ initial pixel positions in the first column

$j \leftarrow 1$

while $j < T - 1$ **do**

$i \leftarrow 0$

while $i < D$ **do**

 ▷ tracking loop

$p[i][j] \leftarrow p[i][j - 1] + \text{rint}(d[i][j - 1])$

 ▷ "move" previous pixel position

$s[i][j] \leftarrow p[i][j - 1] - p[i][j]$

$i \leftarrow i + 1$

end while

$i \leftarrow 0$

while $i < D$ **do**

$s[i][j] \leftarrow s[i][j] - s[i + (D/2)][j]$

 ▷ subtract by second half

$s[i][j] \leftarrow s[i][j] / (D/2)$

 ▷ divide by half D

$s[i][j] \leftarrow s[i][j] * w[i][j]$

$i \leftarrow i + 1$

end while

$j \leftarrow j + 1$

end while

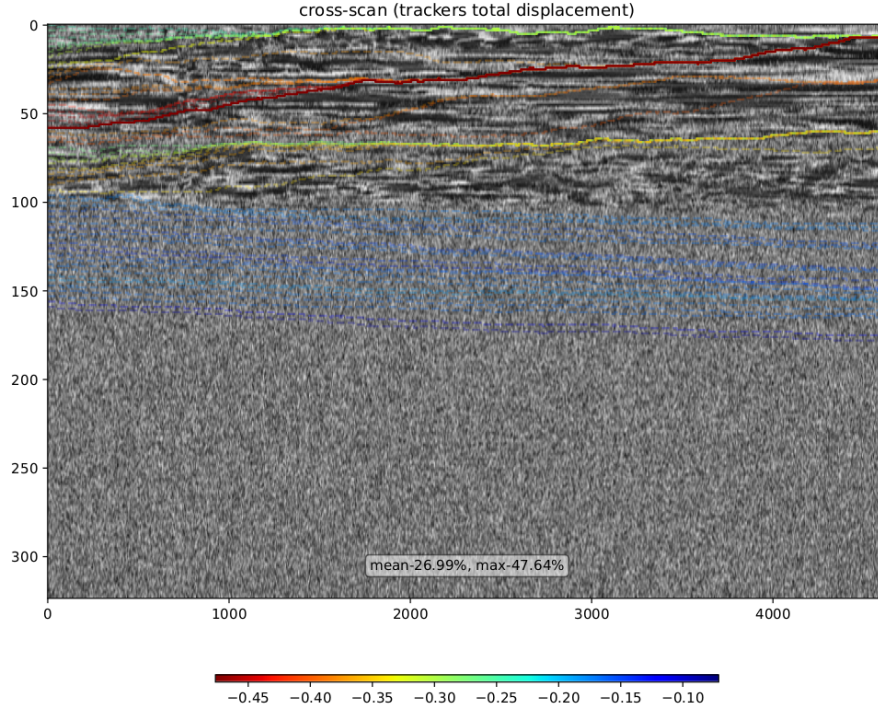


Fig. 2.10: A phase gradient image of the local strain, computed by the *pixel tracking* algorithm. Pixels from the leftmost column ($x = 0$) were tracked according to the phase gradient in the next column and so on. This led to the characteristic "traces" of displacement from left to right (colorized). The blue lines depict the random displacements from OCT noise. We computed the strain again from the FD of the upper half to the lower half of the imaging depth. We then either picked the trace with the largest total strain over time, or the mean of all strains which were traced. Both results are shown on the bottom legend.

Since our goal was the elasticity at selected grid points, although we took depth-resolved strains, we needed to cumulate our strains to a flat-resolved strain scalar for a comparable pseudo-stiffness value. Cumulation methods included the sum, mean, median, or their weighted forms accommodating for the different visibility at different points within the object. In the end, an ω -weighted mean over the total clipped depth D_c (y-axis) and then the sum over all scans T (x-axis) produced a suitable result:

$$\epsilon_{cum} = \sum_{t=0}^T \frac{\sum_{z=i}^{D_c} \omega(z, t) * \epsilon(z, t)}{\sum_{z=i}^{D_c} \omega(z, t)} \quad (2.3)$$

2.4 Test Objects

Compression was generated by the indenter, but was exhibited in the test object. We used animal organs and tissue-mimicking phantoms, the latter of which we produced timely in our laboratory:

- Six *plastisol phantoms*, mixed with a hardener for different stiffnesses, and with titanium dioxide (TiO_2 , dosed with a 0.1 ml microspoon) for different opacities in the following ratios:

Tab. 2.1

id	hardener [%]	plastisol [g]	hardener [g]	TiO_2 [0.1ml]
P0	0	30	0	1
P5	5	28.5	1.5	2
P10	10	27	3	3
P15	15	25.5	4.5	4
P20	20	24	6	5
P25	25	22.5	7.5	1

- Three *gelatine phantoms*, mixed with tap water for different stiffnesses, and with TiO_2 for different opacities in the following ratios:

Tab. 2.2: (titanium dioxide dosed with a 0.1ml-microspoon)

id	gelatine [%]	gelatine [g]	TiO_2 [0.1ml]
G5	5	2.63	1
G10	10	5.56	3
G15	15	8.77	5

We palpated each phantom *five times* at a single central target point.

- One *chicken heart* (45mm) flatly fixated onto the styrofoam ground by 3 pins and palpated at max. 0.3 N force-at-shaft, in a 8 x 1 grid of evenly distributed target points.
- One *chicken stomach* (85mm) flatly fixated onto the styrofoam ground by 3 pins and palpated at max. 0.3 N force-at-shaft, in a 10 x 5 grid of evenly distributed target points.
- One *chicken liver* (85mm) flatly fixated onto the styrofoam ground by 3 pins and palpated at max. 0.01 N force-at-shaft, in a 7 x 7 grid of evenly distributed target points.
- One single *lamb testicle* (105 mm), modified with a local stiffer inclusion (ca. 10 x 10 mm), which was created by a hardened glue, injected with a syringe ca. 10 mm inside the organ to mimic a tumor lesion. The hardened glue is extra stabilized with crumbled aluminum foil to prevent push-away by the indenter. It was flatly fixated onto the styrofoam ground by 2 pins and palpated at max. 0.5 N force-at-shaft, in a 8 x 5 grid of evenly distributed target points.

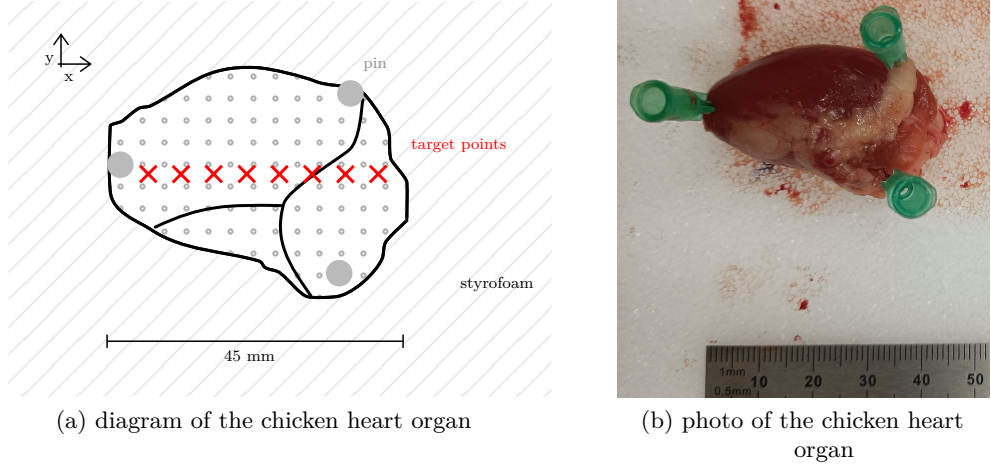


Fig. 2.11: To the left (a), a diagram of the chicken heart is shown with the planned 8 target points (red), which were to be palpated. 3 pins (grey) stabilized the organ onto the styrofoam at three different anchor points. To the right (b), an actual photo shows the organ and its length.

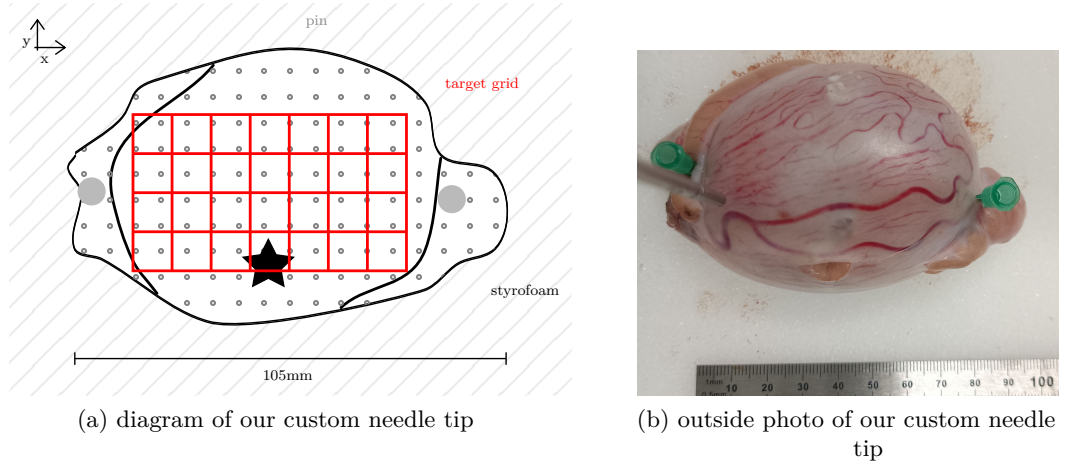


Fig. 2.12: To the left (a), a diagram of the lamb testicle is shown with the planned grid (red) of 40 target points, each represented by the crossings of the grid. 2 pins (grey) stabilized the organ at 2 different anchor points. A star (black) depicts the location of our stiff inclusion. To the right (b), an actual photo shows the organ and its length.

We palpated each organ only *once* at every target point inside the grid.

Tab. 2.3: overview of the different organs and their palpations

description	length [mm]	grid	max. shaftforce [N]
chicken heart	45	8 x 1	0.3
chicken stomach	85	10 x 5	0.3
chicken liver	85	7 x 7	0.01
lamb testicle (modified)	105	8 x 5	0.5

3 Results

3.1 Force estimation

For the force-at-tip estimation, we employed a simple linear regression by least squares for each phantom palpation to relate between the microscale compression of the *needle* and the force measured at the *shaft* sensor. This means again that we estimated how much specific force is needed to displace the needle tip for a specific length. This was represented in the a_F -coefficient of the linear equation 2.2. (We omitted the constant component because there is no translation from both starting points: Both start at zero force or length). For more accurate results, we ensured that no rupture of the phantom surface happened and only uniaxial force acted. With center wavelength $\lambda_0 = 1.325 \cdot 10^{-6}$ m and refractive index $n = 1.5$, we then took the ordinary mean of all the a_F -coefficients for a calibration result $\bar{a}_F = 2412165$.

$\bar{a}_F$ was then used in the organ palpations afterwards as the conversion coefficient in the same linear equation, but for different displacements. The needle was therefore calibrated in the first of the two linear calibrations.

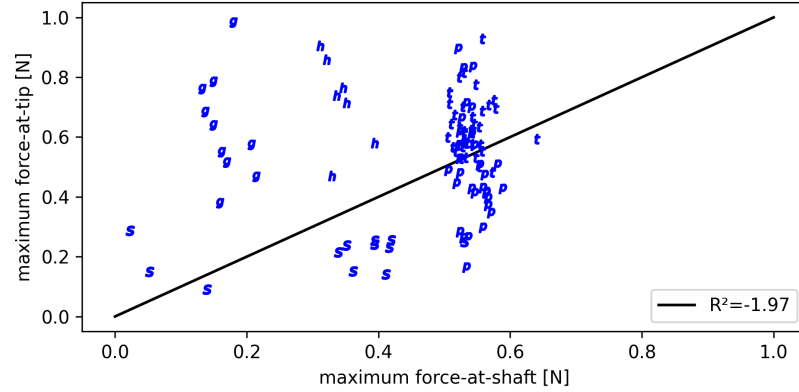


Fig. 3.1: Here we see the maximum force measured at the *shaft* by the mounted shaft sensor (x-axis) and the maximum force at the *tip* measured by OCE (y-axis) for each palpation (blue data points, p=plastisol, g=gelatine, h=heart, s=stomach, t=testicle, liver omitted). In a perfect world, all points would fall onto the black identity line ($y = x$), meaning a perfect prediction. Our points falling out of order indicates a bad prediction, which is also shown by the R^2 -value in the legend. Since we aimed our shaft force to be at 0.1 N, 0.3 N and 0.5 N, we can rule out a shaft force sensor malfunction because of the three vertical point cumulations (ignoring the two zero measures of the stomach). Although being all over the place, the tip forces are correctly inside the limits $[0,1]$. Generally, lower tip forces are overestimated and higher tip forces misestimated, even for the training data (phantoms).

3.2 Stiffness estimation

For the second calibration, we separated the data into the phantom indentations (plastisol and gelatine), which we call the *training data*, and into the organ indentations, we which we call the *prediction data*. We used the training data to create the second model by simple linear regression. For that, we also employed a least squares estimation. We then plotted the trained result in a graph between the measured attribute, for example the *pseudo-stiffness* by the maximum pixel tracking method, and the linearly predicted Young's modulus. In the same diagram, we plotted the linear regression of the prediction data, to see how well they would compare. For that, we took the R^2 value, an indicator for the accuracy between the model and the data it is based on - in other words, how well the regression "fitted". This accuracy value typically lies between 0 (bad) and 1 (good). If the value is negative, it means that just a horizontal line would perform better. We also took another R^2 value between the model and the prediction data to see how well the model would have fitted the prediction data.

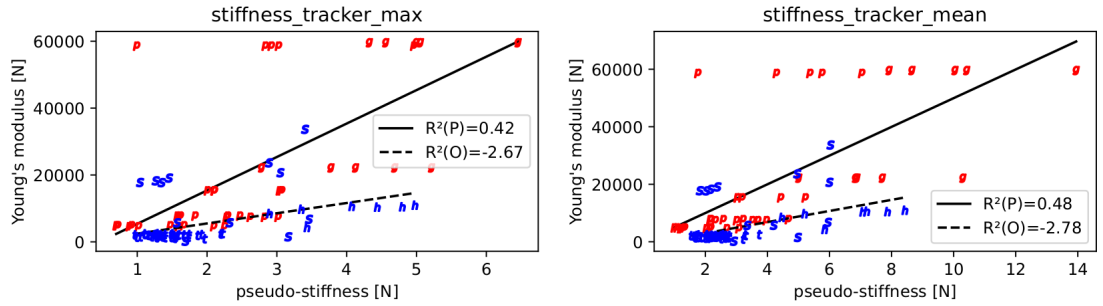


Fig. 3.2: Here we see our second calibration (black line) between the measured pseudo-stiffness (on the x -axis) and the predicted Young's modulus (on the y -axis). We measured the pseudo-stiffness by tracking the maximum displaced pixel (left) or the ordinary mean of all displaced pixels (right) over time. Each palpation is represented by a data point with the respective first letter of the test object (p=plastisol, g=gelatine, h=heart, s=stomach, t=testicle, liver omitted). The accuracy value R^2 of the model to the training dataset (P=phantoms, in red) and to the prediction dataset (O=organs, in blue) are shown in the legend. We can see an obvious skew by the stiffer phantoms - they "pull" the linear fit line to the top by having the same pseudo-stiffness, either by observing the same strain, or by "feeling" much lower force-at-tip, or both. Overall, this results in a significant underestimation of high Young's moduli which are greater than 50 kPa.

3 Results

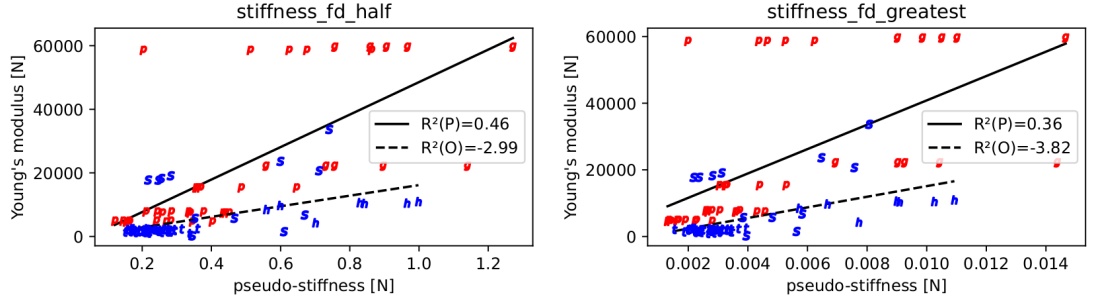
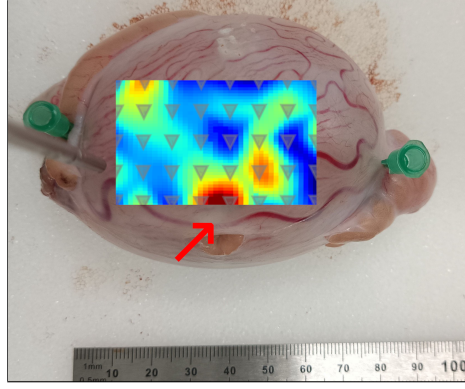
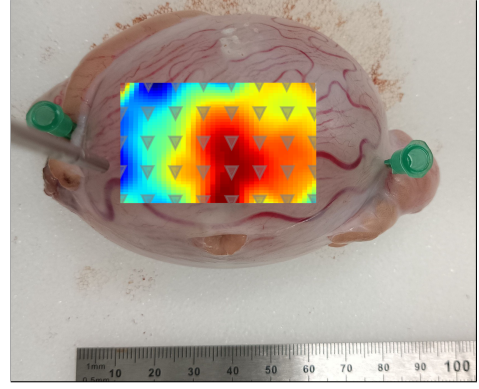


Fig. 3.3: Similar to Fig. 3.2, we show our second calibration (black line) between the measured pseudo- stiffness (on the x-axis) and the predicted Young's modulus (on the y-axis). The difference is, that we here measured the strain according to the finite-difference method of [4]. As we saw it, the accuracies look very similar. The underestimation of high Young's moduli is also apparent.

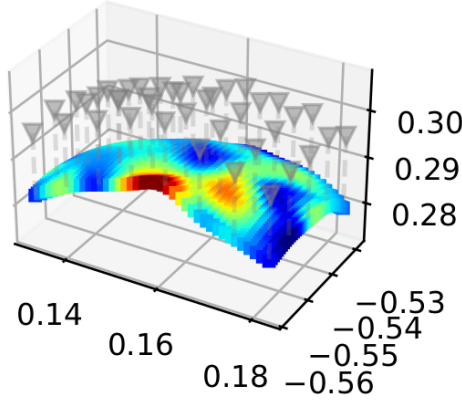
Overall, we did this training for each measured attribute from which we tried to derive the Young's modulus. We then plotted the predicted Young's moduli against the spatial data of the robot end-effector and achieved 2-dimensional ("top-down") or 3-dimensional elastograms. We then overlaid the 2-dimensional elastogram with the photo of the organ, also taken from above. For a comparison, we generated elastograms and overlaid photos exactly like that, but with the Young's moduli calculated from the reference ball indenter. These were our qualitative results. For the quantitative results, we plotted our predicted Young's moduli against their counterpart from the reference measure.



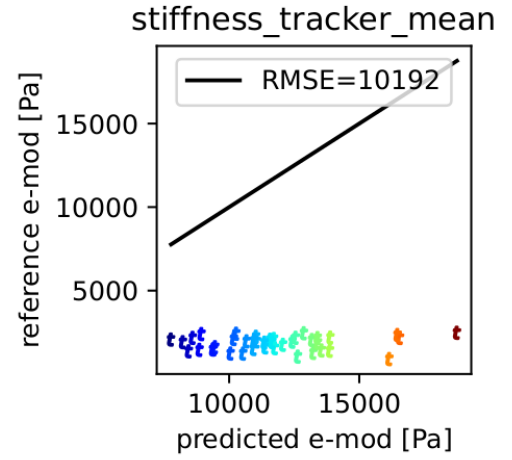
(a) lamb testicle photo, overlaid with the predicted Young's moduli (a red arrow points at its injected inclusion)



(b) lamb testicle photo, overlaid with the reference Young's moduli

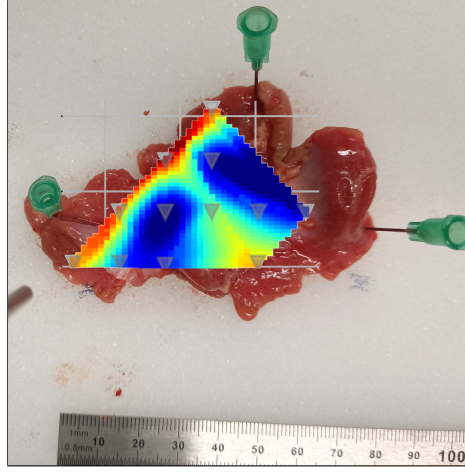


(c) lamb testicle, predicted 3d surface elastogram

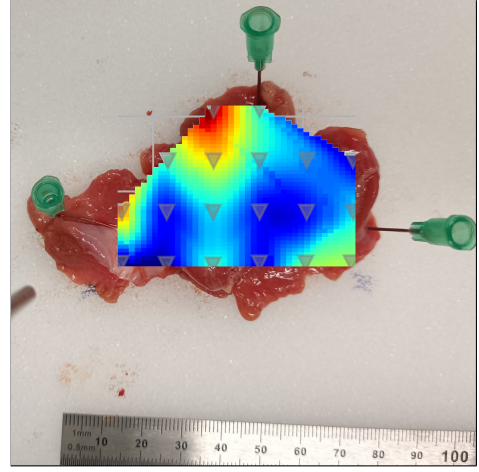


(d) predicted Young's moduli against their reference Young's moduli, colored according to the predicted values and with an identity graph (black), where a perfect prediction would be $(x = y)$

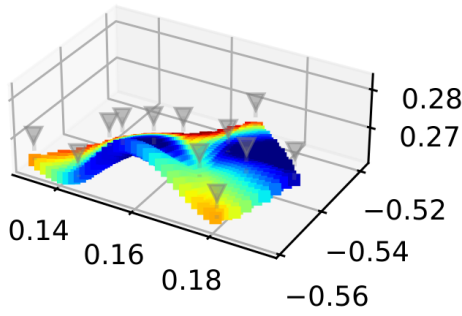
Fig. 3.4: At a glance, we can see here the qualitative (a-c) and quantitative (d) results of our Young's moduli prediction for a lamb testicle, namely three elastograms and a plot of the values. Each grey triangle represents a single palpation. As expected, our needle indenter allowed a more distinct segmentation, which can also be seen in the broader distribution of the plot on the x-axis. However on the y-axis, surprisingly, the values are much more compact. This means, that these reference measures failed to register not only our stiff inclusion, but also *any* strong difference in elasticity. This might be organ-specific.



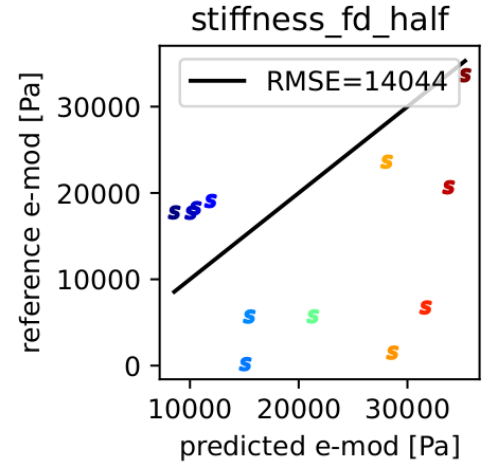
(a) chicken stomach photo, overlaid with the predicted Young's moduli



(b) chicken stomach photo, overlaid with the reference Young's moduli

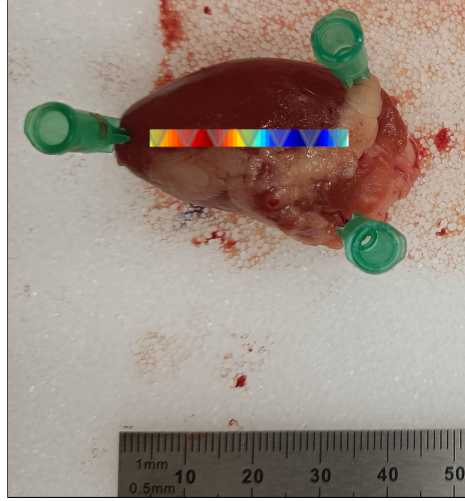


(c) chicken stomach, predicted 3d surface elastogram



(d) predicted Young's moduli against their reference Young's moduli

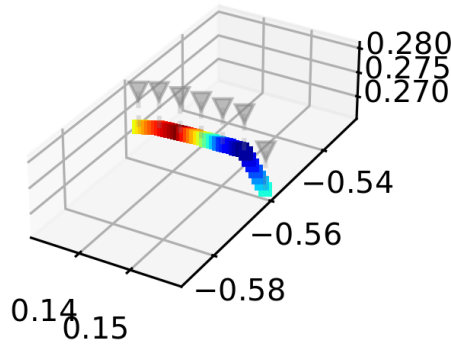
Fig. 3.5: Similar to Fig. 3.4, we can see here the qualitative (a-c) and quantitative (d) results of our Young's moduli prediction, but for the chicken stomach. This organ was noticeably thinner, so that the styrofoam ground, which was not easily strained with our needle, caused the overestimation of stiffness, or even failing measures: We can see missing palpation points (grey triangle) from the originally rectangular grid. However, we can also see a more accurate estimation of the softer and thicker parts of the stomach (blue).



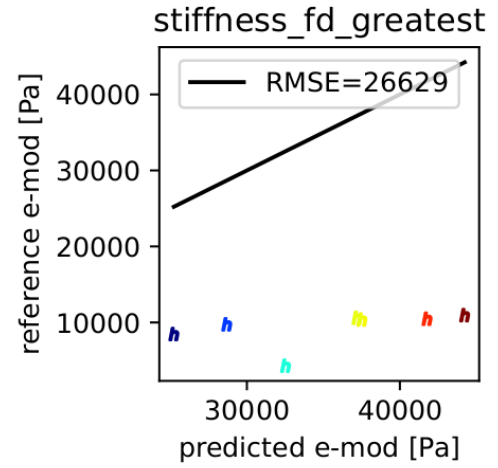
(a) chicken heart photo, overlaid with the predicted Young's moduli



(b) chicken heart photo, overlaid with the reference Young's moduli



(c) chicken heart, predicted 3d surface elastogram



(d) predicted Young's moduli against their reference Young's moduli

Fig. 3.6: Similar to Fig. 3.4, we can see here the qualitative (a-c) and quantitative (d) results of our Young's moduli prediction, but for the chicken heart. This organ was smaller and because of that, we were only able to palpate along one direction. Like the other organs, the predicted elastograms show a more distinct segmentation, especially at 10mm. Also, similar to the lamb testicle, the reference measures are only limited to a small interval (around ca. 10 kPa).

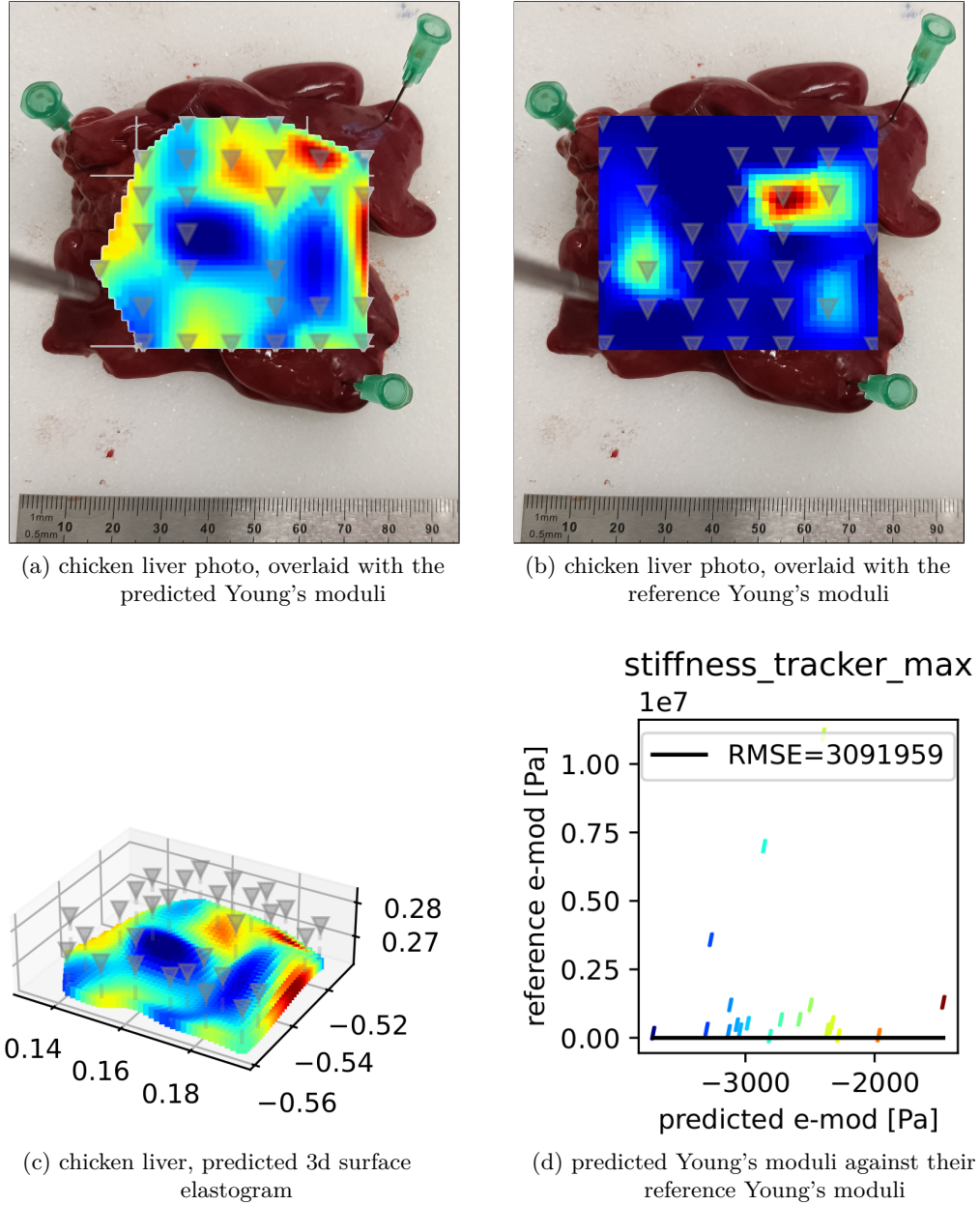


Fig. 3.7: Similar to Fig. 3.4, we can see here the qualitative (a-c) and quantitative (d) results of our Young's moduli prediction, but for the chicken liver. Additionally to being less distinct, the reference elasticities of the target points were impossibly high up to a magnitude of $1e^7$. Because of imminent ruptures in the organ, we had to lower the palpation force to a very small maximum of 0.01 N, which is barely the resolution of the shaft force sensor. This also led to the underestimation of the predictions with negative values. In the end, we had to ignore these results in our calibrations.

4 Discussion

Coming to the discussion of our results, we start with the suitability of the selected test objects to our elastography methods.

4.1 Test objects

The plastisol phantoms, which we prepared on our own, were quite durable and long-lasting. We can attest to an increased resistance to rupture when mixed with a greater ratio of hardener to plastisol. Our gelatine phantoms of porcine origin were easier to produce, but showed a significant lower longevity and durability. They were prone to rupture and elasticity changes over time and use. We noticed difficulties in the strain estimation if we used too much titanium dioxide: The high opacity worsened the visibility of our OCT light.

The elasticity of our chicken stomach was heterogeneous, but had very thin spots where both force sensors quickly overestimated because of the closing distance to the ground. Additionally, due to the same reason, strain was underestimated at the same spots. This resulted in an extra overestimation of the Young's modulus, which consisted of those two factors. The chicken heart was small and narrow in width but it showed a heterogeneous elasticity along its limited length. Single stiffer areas were recognized. The modified lamb testicle was rounder and had a very slippery surface. The edges made it difficult for the needle to grip and the fluid-like behaviour inside the organ made it initially possible to push-away our stiff inclusion. For that reason, we stabilized the inclusion with crumbled aluminum foil to hold it in place. The elastograms then showed a clear heterogeneity and good visibility. The chicken liver was too soft and fast to rupture. We deemed it impossible to palpate with our needle due to the low force we were allowed to use. We often missed the contact points due to the low resistance of the surface. That means, our recording started with the indenter already inside the organ and ended with the surface ruptured by the indenter. It made no difference which indenter we used. This might improve with a better shaft sensor or a better actuation program. We further evaluate our actuation process and its suitability to our elastography methods.

4.2 Actuation

The robotic actuation showed superior accuracy and precision. Its programmability was flexible enough to adjust to different palpation requirements depending on the form, grip and visibility of the object. As expected, the positions of the end-effector were reliably and accurately recorded. Errors and limits were communicated early and verbose. But except for the shaft force contact, we were not able to automatically determine earlier contact points for the start of our strain estimation. For example, we had a distortion interference when the object reflection was at the same distance where the force reflection

was multiplexed to. This falsely registered an increase of the force-at-tip without the needle even touching the test object.

However, with the actuation *relaxing stage* and enough visibility, the strain information was present in the OCT records, but it could not be automatically isolated. We believe an early start of the strain estimation interval to be crucial: A typical misestimation of the elasticity appeared when the training data did not account for greater strain differences. For accurate measurements, we not only need to capture, but also process the whole strain build-up. Especially the initial surface indentation may prove characteristic of its overall elasticity. Otherwise, only a small portion of the build-up is evaluated and this might be insufficient for quantification training. Going further in the actuation program, we evaluate the retract point: Depending on the preprogrammed maximal shaft force, which was specific to each test object, most object palpations showed no to minimal damage: Tear and rupture had been prevented with an appropriate force limit setting and a sufficient shaft force sensor resolution. At the target point, if either the maximum indentation depth is reached or the maximum force-at-shaft is *not* reached, it successfully signalled damage or an overly thin region. The respective palpations were then not evaluated anymore. We have seen this especially with the chicken stomach or chicken liver. Additionally, it successfully prevented damage to the ground or indenter.

Relating the synchronous shaft force sensor, its reading showed a reliable tactile contact record depending on the test object resistance, texture and shape. However, the shaft force was often higher than the tip force resulting in a possibly premature stop of the palpation. Additionally, the indentation distances, which were measured during the actuation, were only used in our 3-dimensional elastograms and for the reference moduli. Particularly it was not used in the computation of our local strains since it could not account for bulk motions of the test object. We continue to evaluate the suitability of our OCT data representation and its processing for the elasticity experiments.

4.3 OCT recording

We recorded our spectrograms at a sampling rate of 5.5 kHz, which proved sufficient. It allowed for smaller data sizes and shorter computing time. This meant a faster development with shorter testing loops. We noticed that higher rates did not result in a much better strain estimation to justify the exponential increase in complexity. For even faster computation, subsampling was possible, which we also employed successfully. At lower rates, the phases and intensity changes between the A-scans might appear disruptive, but since we only unwrap and cumulate the phases changes in the uniaxial direction, the strain estimates scale proportionally with the sampling rate s by a linear factor η . This means, the pseudo-stiffness also scaled that way, but inverse (given a uniform force). Therefore, we only needed to calibrate the conversion once at $s = 5500$, and adjust the predicted Young's modulus by a $\frac{1}{\eta} = \frac{s}{5500}$ when we changed s :

$$E_s = \frac{E_{5500}}{\eta} \approx \frac{F}{\eta * \epsilon_{5500}} \quad (4.1)$$

In earlier experiments, where we tried to automatically detect the visual contact point with the object, lower sampling rates decreased the chance of finding it: Namely, we tried to deduce it from a greater phase change in *horizontal* direction, which is directly affected by the timeskip between A-scans. In hindsight, this method proved too unreliable. Next,

we evaluate our processing of the raw OCT data.

4.4 OCT processing

With the spectrograms fourier-transformed, the intensity data showed an orientation to the object pre-contact, actual contact and the needle tip compression. Their data also served as viable strain weights to further tell strain apart from background noise. This noise was especially tenacious in the phase data: Without denoising, we basically saw displacement everywhere. This would have led to significant strain overestimations if we had not applied a 2-dimensional median filter. But there was a limit: We could not overcome the major artifacts in the inner-needle displacement signal with our simple denoising. Those led to significant force-at-tip misestimates. Other than that, the unwrapped phases were continuous enough to allow a certain pixel trackability along the scans. This was possible even in deeper regions where the intensity showed no distinction in the particle displacements or their directions. This is also a reason for us to use the intensity images only for previews and weighting, but not for the actual displacement correlation. For that, we used the phase information. In the following section, we will go into a little bit more detail about the suitability of our spatial multiplexed force signal and its phase.

4.5 Force-at-tip estimation

At first, it seemed to us that the spatial multiplexing of the OCT signal was sufficiently distinguishable: Most of the time, the slower and smaller displacements in and of the glass had a strong contrast to the larger object displacements in the background. Additionally, because of the way both signals are referenced by an external mirror, the force-at-tip signal showed a strong phase-shift in the other direction. In other words, if closing test objects created a negative phase change, the closing glass inside the needle created a positive phase change. However, the near-rigid needle hull with its small perforations showed only a very small linear phase gradient. It quickly reached a point where further displacements were harder to achieve with increasing force. Consequently, the respective forces-at-tip were more difficult to determine. Additionally to that, the first force to noticeably compress the needle hull had to pass an initial threshold which delayed feasible readings. All these limitations contributed to a lower sensitivity of the tip sensor. Another aspect was that because of the small displacement interval, small variations (for example by noise) already created large force-at-tip variations. This impacted the sensor as early as in its calibration. If we could overlook those aspects, there would still be the occasional multiplex artifact. Overall, our final force estimates were badly calibrated. Possibly, instead of taking one mean of multiple linear regression results, we could have taken the maximum force values at each palpation and only then fit a single linear regression for a more compact model. Instead, we tried to also represent the whole force increase over time in the calibration, which may have introduced too much noise.

All this had a major influence on our pseudo-stiffness: For example we had force-at-tip estimates which were even greater than the acting shaft force. However, this had no effect on our strain estimates and we were able to evaluate both elasticity factors independently of each other. In the next paragraph, we evaluate those methods of strain estimation.

4.6 Strain estimation

The signal phase in the object mostly showed a distinct and processable change during the indentation in most of our test objects. As expected, visibility quickly decreased over the imaging depth, but not over the indentation depth. We assumed that the depth of the maximum detectable displacement served as a very simple indicator for that visibility. In other words, below that, lower displacements were a sign of a fading signal strength. This means that visibility changes significantly impacted the strain we could detect, which were otherwise robust over successive indentations. Of the different strain estimation methods, none could sufficiently recognize the highest elasticity values greater than 50 kPa. We believe that since we necessarily took the force-at-shaft as the starting point, the strain analysis interval was too short, and an earlier start would improve the prediction accuracy with more processable strain. The problem that we faced was that different elasticities were wrongly assigned the *same* amount of strain, which were missing a crucial part of softer deformations: Those could not be registered with the less sensitive force-at-shaft sensor, or even the noisy force-at-tip sensor. One solution could be to manually mark each time the needle enters, either on the A-scan or at the actuation time, but this again depends on subjective judgement.

Astonishingly, all four methods produced similar qualitative results otherwise. We would rather improve on our choice of model for the elasticity predictions: A simple linear regression, which allows negative values, does not suit a strain trend which resembles more a logarithmic or logistic growth over time. Adjusted linear models or even non-linear models could be a better fit. We might also see more accuracy if we rather calibrate to a subset of specific tissue. In other words, train better models on stiff cancer tissues to better detect and measure those cancer tissues.

Now both force-at-tip variations (by indenter structure) and strain visibility variations (by object composition or observation interval) influenced the accuracy of our pseudo-stiffness. Other forces had no noticeable impact. This means, that with more sensitive force sensors, surface penetration with similar needles for a deeper imaging might be possible. However, since we only computed a flat elasticity without depth context, a simple 2-dimensional representation proved sufficient for showing qualitative differences in tissue elasticity. The evidence is in the correlation of our predictions with the reference values, even the non-plausible ones. Most strain distortions came rather from shape and texture of the object. When we moved to a 3-dimensional representation, since our palpations were well-actuated, programmed and configured beforehand, they allowed for shallow elastograms of otherwise overlapping depth information, but it should be straight-forward to incorporate them into true 3d imaging. In general, elasticity data was now shown to be contextual and quantifiable (albeit with resolvable limitations), which is recordable, comparable and further processable.

We will now try to conclude our work in the next chapter.

5 Conclusion

The elastography results we achieved by our specific needle design indicated a sufficient ability in objective tissue differentiation. The 2-dimensional visualization of depth-resolved elasticity showed enough segmentation for the localization of stiffer regions. The estimation of the force-at-tip by the phase-resolved OCE technique and the estimation of induced strain by the same technique produced most of the time a comparable pseudo-stiffness $\hat{E}$, which suggested enough specification to enable differentiation, recognition and segmentation of palpable tumor-like tissue in organs, but not yet an accurate quantification into *Young's moduli*: Higher elasticities were significantly underestimated. We suggest the analysis of earlier and more strain. We also suggest improvements to the multiplexing, range and resolution of the force-at-tip sensor, which we otherwise found to be too insensitive and noisy. Imprecision and inaccuracy of that sensor due to non-linear behaviour in an otherwise linear force-conversion might also be compensated with a more accommodating design: A metallic needle hull like ours might not be compressible enough for a necessary sensitive force-at-tip sensor.

An increase of OCT visibility depth by penetrating indentation also seemed feasible. We might improve the results with a 3-dimensional data representation for more contextual data: Additional quantified data points of strain in the object depth might allow for non-linear prediction models to form, e.g. as datasets for machine learning. Also, asynchronous processing of large OCT data was sufficient for sequential elastography: We saw no need for simultaneous monitoring.

Needle C-OCE in heterogeneous organs was also made difficult by their specific shapes: At some organs, *obliqueness* subsequently caused indenter slips or misses. Ground proximity impacted the accuracy of our results negatively. Specific *textures*, e.g. overly smoothness, also caused slips or misses, or object bulk movements ("push-away"). Specific *proneness* to tear or rupture quickly caused ground proximity and non-linearity especially in very soft tissue like a chicken liver. Specific visibility loss in very *opaque* tissue also caused displacement and strain misses especially in deeper regions, which resulted in elasticity underestimates.

Overall, we identified many advantages of qualitative and quantitative needle C-OCE, but also a number of challenges, which after being resolved, can attest to its potential usage in the clinique. That being said, further research is necessary, whose direction we laid out to some extent.

Listings

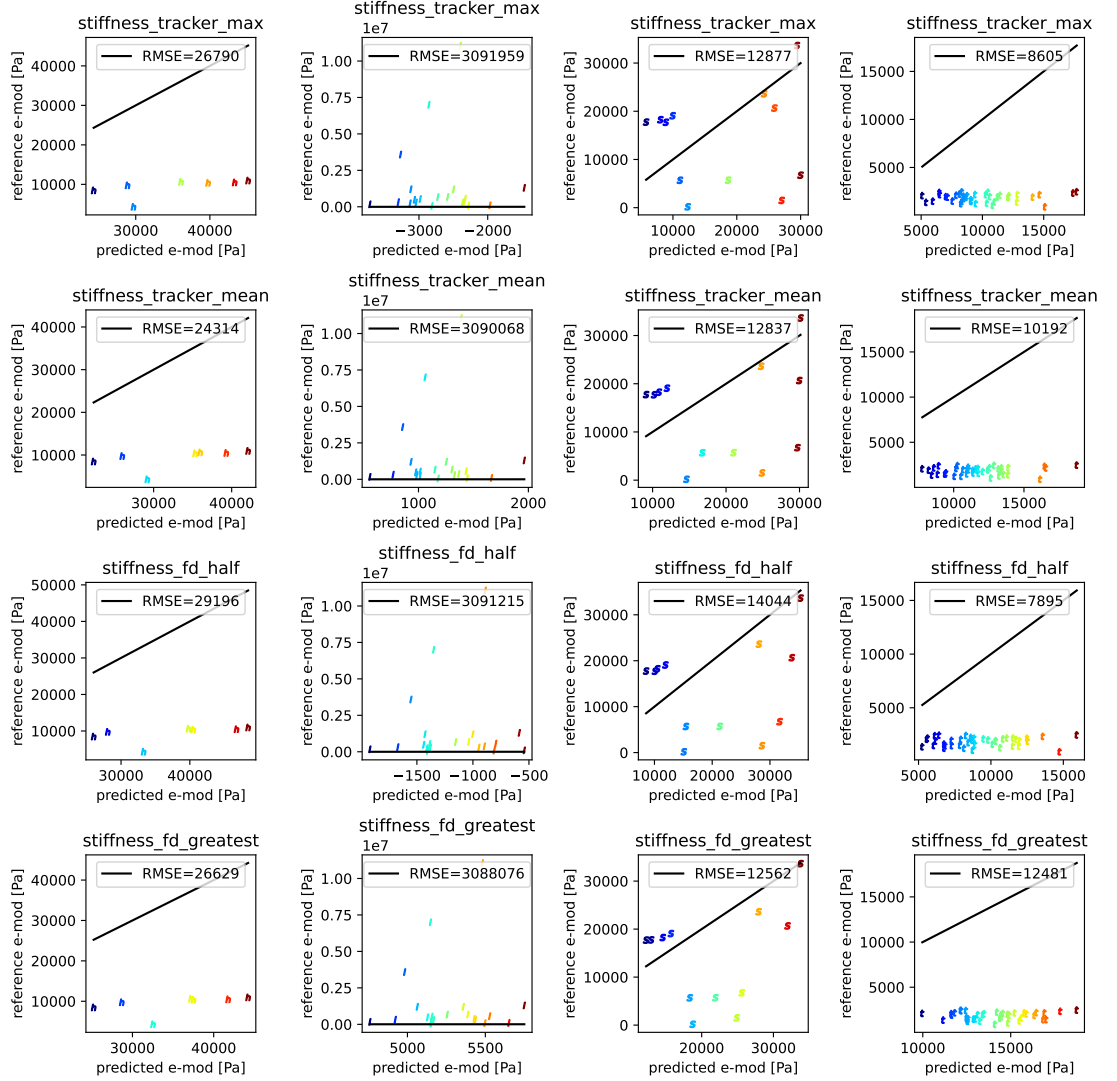


Fig. 1: Prediction results for Young's moduli from our pseudo-stiffnesses, grouped by the organ (column) and the strain estimation method (row). The black line depicts the identity curve ($x = y$), where a perfect prediction would be.

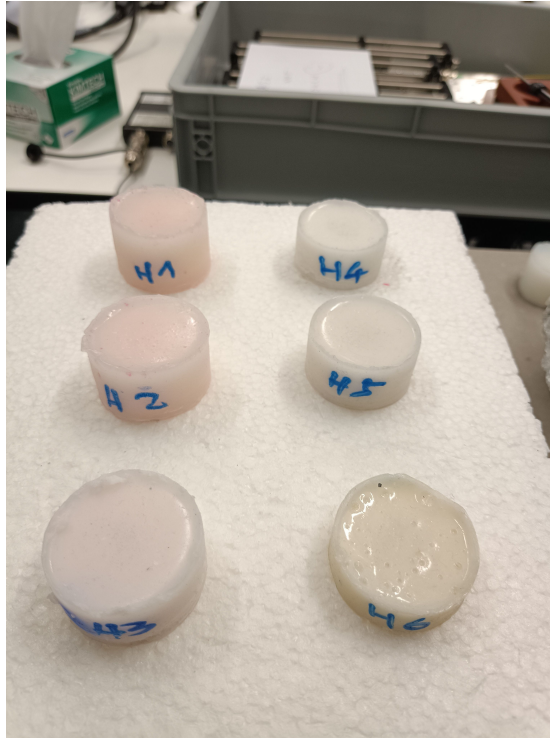


Fig. 2: A photo of our custom plastisol phantoms, sorted by elasticity. H1-H6 correspond evenly to P0-P25 of table 2.1.



Fig. 3: A photo of our custom plastisol phantoms, sorted by elasticity. From left to right, they correspond evenly to G5-G15 of table 2.2.

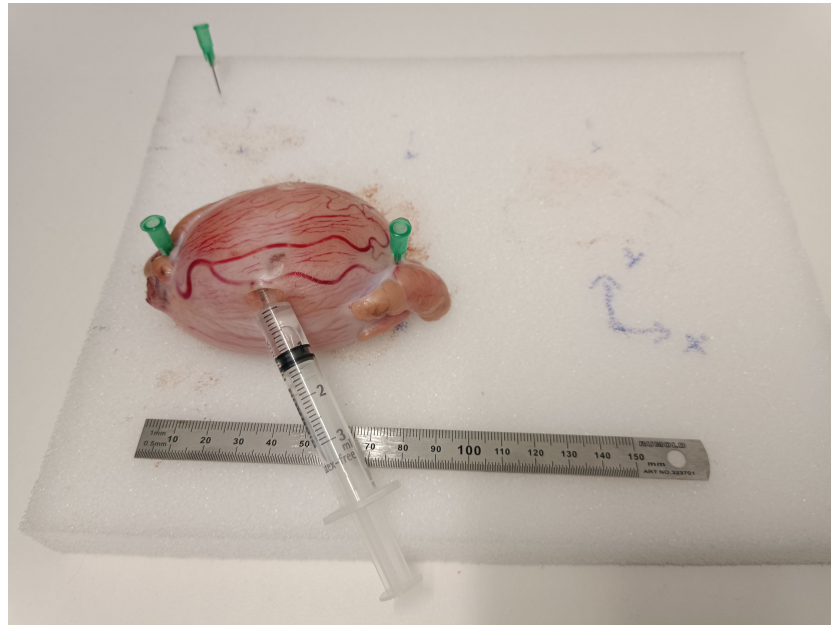


Fig. 4: A reenactment photo of the lamb testicle injection with a syringe through a cut at its surface. The injected glue then stiffens as it hardens and is detectable from the outside by palpation.



Fig. 5: A photo of our full setup in our laboratory at MTEC. We can see the KUKA robot arm standing on a scaffold with its computer below. The needle is mounted as the end-effector. An OCT fiber (yellow) leads to the OCT device (not seen) and a black cable leads from the force sensor at the needle shaft to its receiver (not seen). A lamb testicle lays fixated on a thinner styrofoam plate, which can be replaced for sanitary reasons. Below, there is a thicker styrofoam plate for leverage. A large green cloth covers the rest of the table.

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Declaration

Hiermit versichere ich, dass ich meine Abschlussarbeit selbständig verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.



Datum: 31. Januar 2025

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(Unterschrift)