Third Joint Eurohaptics Conference and Symposium on Haptic Interfaces
for Virtual Environment and Teleoperator Systems
Salt Lake City, UT, USA, March 18-20, 2009

Quantifying Perception of Nonlinear Elastic Tissue Models using Multidimensional Scaling

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Abstract

Simplified soft tissue models used in surgical simulations cannot perfectly reproduce all material behaviors. In particular, many tissues exhibit the Poynting effect, which results in normal forces during shearing of tissue and is only observed in nonlinear elastic material models. In order to investigate and quantify the role of the Poynting effect on material discrimination, we performed a multidimensional scaling (MDS) study. Participants were presented with several pairs of shear and normal forces generated by a haptic device during interaction with virtual soft objects. Participants were asked to rate the similarity between the forces felt. The selection of the material parameters – and thus the magnitude of the shear and normal forces – was based on a pre-study prior to the MDS experiment. It was observed that for nonlinear elastic tissue models exhibiting the Poynting effect, MDS analysis indicated that both shear and normal forces affect user perception.

Index Terms: H.1.2 [Information Systems]: User/Machine Systems—Human Factors; I.6.5 [Computing Methodologies]: Simulation and Modeling—Applications; J.2 [Computer Applications]: Physical Sciences and Engineering—Mathematics and Statistics

1 Introduction

Surgical simulation systems [1, 16] are an attractive option for surgical training and pre-operative planning. They allow real-time visualization of the surgical procedure and, in some cases, provide force feedback to the user. The development of realistic simulation systems providing appropriate haptic feedback requires accurate modeling of soft tissue and its interaction with the surgical tools.

Human organs in general are inhomogeneous, anisotropic, and exhibit nonlinear viscoelastic properties [7]. Due to computational requirements, simplified models are frequently used to model tissues for simulating surgical procedures, such as mass-spring-damper models [8]. However, there are several key differences between such approximations and accurate tissue representations. One is the Poynting effect, which describes the presence of both shear (tangential) and normal forces during tissue shearing. This effect can be described with nonlinear elastic tissue models, but not with linear models. Figure 1 provides a visual representation of the forces developed while shearing a nonlinear elastic virtual model. We demonstrated this effect in [18, 20]. We considered palpation of bovine myocardial tissue and Sylgard 527 gel samples, which are often used as models for human heart and brain tissue. It was observed that the normal forces developed during shearing of myocardial tissue are significantly larger than the absolute human perception threshold for force discrimination [11].

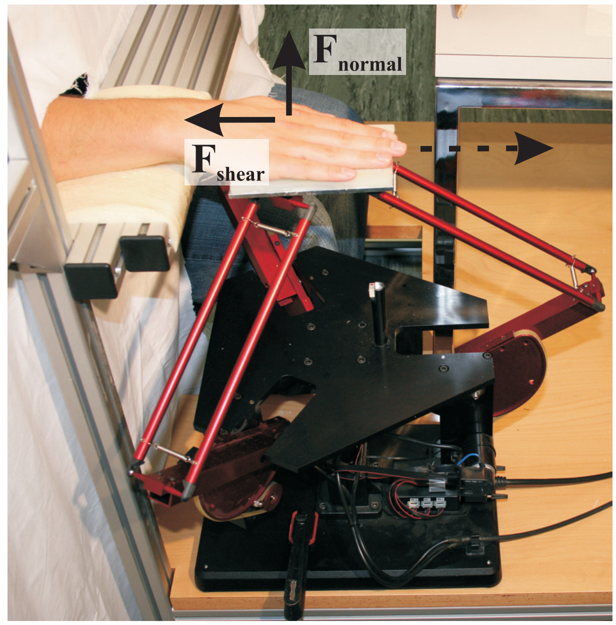

Figure 1: The Delta haptic device used for psychophysical experiments. As the user interacts with the nonlinear elastic virtual model and moves the device, normal (F_{normal}) and shear (F_{shear}) forces are generated due to the Poynting effect.

The Poynting effect is significant for some organs but may not be for others. This motivates the study of humans interacting with nonlinear virtual tissue models with varying values of shear and normal forces, in order to understand the impact of the Poynting effect on surgical simulators. The importance of the effect for achieving optimal training with a surgical simulator is also relevant.

In this study, we quantify the impact of shear and normal forces resulting from the Poynting effect on user perception with a multidimensional scaling (MDS) study. MDS is a family of algorithms that take proximities between pairs of objects as inputs and evaluate the coordinates of the objects embedded in a multidimensional space [3]. MDS provides information about the dimensionality of the perceptual representation and is used here to assess the relevance of the Poynting effect. In the MDS experiment, different combinations of shear and normal forces are presented to users. In order to select the reference forces for the experiment, a force discrimination pre-study was performed.

The remainder of the paper is organized as follows: Section 1.1 describes prior work related to our study. The key derivations for the constitutive law of a body undergoing simple shear are presented in Section 2. The psychophysical experimental setup is described in Section 3. Details and analysis of results of the pre-study

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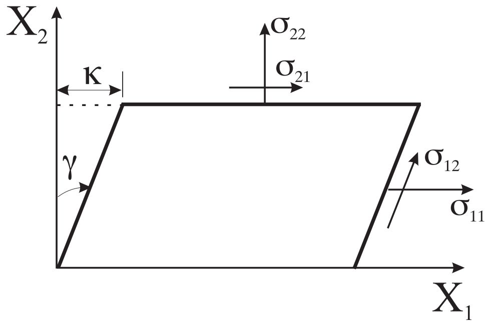


Figure 2: Two-dimensional representation of a body undergoing simple shear; the shear strain is κ in the X_1 direction.

as well as the MDS study are given in Sections 4 and 5, respectively. Finally, Section 6 summarizes the work done and provides possible directions for future work.

1.1 Related Work

Significant work has been performed in the area of modeling deformable bodies for surgical simulation. Most of the past research has generally assumed linear elasticity for modeling tissues. Misra et al. [19] provide an overview of organ modeling methods for surgical simulation. In addition to work done by Misra et al. [18, 20], Dehghan and Salcudean [4] have compared the effects of linear and nonlinear finite element models on mesh displacement during needle insertion. They concluded that, in the presence of asymmetric boundary conditions, there are noticeable differences between linear and nonlinear models.

Extensive research has also been done to study how materials are perceived by humans, e.g. [13, 14, 23]. Other work has focused on both qualitatively and quantitatively characterizing the efficiency, accuracy, and realism of haptic virtual environments, e.g. [5, 6, 22].

Recently, MDS has been used as a quantitative means of understanding human perception. Pasquero et al. [21] provides a review of MDS analysis techniques. They also applied these techniques to perceptual data collection of a prototype mobile tactile handheld device. Yoshida [25, 26] was one of the first to use MDS techniques for quantifying metallic and fibrous tactile perceptions. Performing MDS analysis on tactile stimuli data, two dimensions: smooth/rough and hard/soft were identified in [10]. Bergmann Tiest and Kapper [2] investigated roughness and compressibility via MDS studies. MacLean and Enriquez [17] used MDS for mapping haptic perception for the design of haptic icons. Leskovsky et al. [15] evaluated the haptic perception of real and virtual deformable objects using MDS techniques. Their analysis showed a clear perceptual distinction between real and virtual objects only when low-fidelity rendering was used in the virtual environment. Also, MDS analysis showed that objects became more distinguishable as the stiffness of the body increased.

The purpose of our research study is to investigate the importance of nonlinear material properties of soft virtual deformable objects while palpating the body using a haptic device. Using MDS analysis we study the impact of the Poynting effect on user perception.

2 The Poynting Effect

In order to highlight the differences between linear and nonlinear elasticity-based tissue models, this section presents the theoretical relationships for the stresses and strains in a body undergoing simple shear, as shown in Figure 2. Shear is considered because it is common practice for clinicians to palpate and perform a shearing motion on the organ either by hand or with an instrument.

The formulation presented here highlights only key relationships and does not cover the fundamentals of continuum mechanics. For further details, we refer the reader to [9, 19]. The body is assumed to shear by an amount κ, and γ is the angle the sheared line makes with its original orientation. The shear strain is given by $\kappa = \tan(\gamma)$.

If $\mathbf{y}$ represents the position after deformation of a material reference initially located at $\mathbf{X}$, we can describe the simple shear motion by

$$\mathbf{y} = (X_1 + \kappa X_2)\,\mathbf{e}_1 + X_2\mathbf{e}_2 + X_3\mathbf{e}_3, \quad (1)$$

where $\{\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3\}$ are the Cartesian base vectors. From (1), the matrix of the deformation gradient tensor, $\mathbf{F}$, is computed as

$$\mathbf{F} = \frac{\partial \mathbf{y}}{\partial \mathbf{X}} = \begin{bmatrix} 1 & \kappa & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \quad (2)$$

The deformation of materials under large strains (>1%-2%) is described by the theory of nonlinear elasticity, and hyperelastic models are commonly used. For a hyperelastic material, the Cauchy stress tensor $\boldsymbol{\sigma}$ can be derived from a strain energy density function W. There are various formulations for W, depending on the material (e.g. Neo-Hookean, Mooney-Rivlin, St. Venant-Kirchhoff, Blatz-Ko, Ogden, and polynomial or exponential form).

In our work we focus on the Mooney-Rivlin model, since it is a common approach to model soft tissue behavior [7]. Using the Representation Theorem [9], the Cauchy stress tensor for homogenous and incompressible hyperelastic material is

$$\boldsymbol{\sigma} = -p\mathbf{I} + 2\left\{\left(\frac{\partial W}{\partial I_1} + I_1\frac{\partial W}{\partial I_2}\right)\mathbf{B} - \frac{\partial W}{\partial I_2}\mathbf{B}^2\right\}, \quad (3)$$

where I_1 and I_2 are the principal invariants, $\mathbf{B} = \mathbf{F}\mathbf{F}^T$ is the left Cauchy-Green tensor, and p is the Lagrange multiplier. The Mooney-Rivlin strain energy density function in terms of material parameters, C_1 and C_2, is given by

$$W = C_1(I_1 - 3) + C_2(I_2 - 3). \quad (4)$$

Using (3) and (4), and applying the boundary condition ($\sigma_{33} = 0$), the stresses in terms of shear, κ, are

$$\sigma_{11} = 2C_1\kappa^2, \quad (5)$$

$$\sigma_{12} = 2(C_1 + C_2)\,\kappa, \quad (6)$$

$$\sigma_{22} = -2C_2\kappa^2. \quad (7)$$

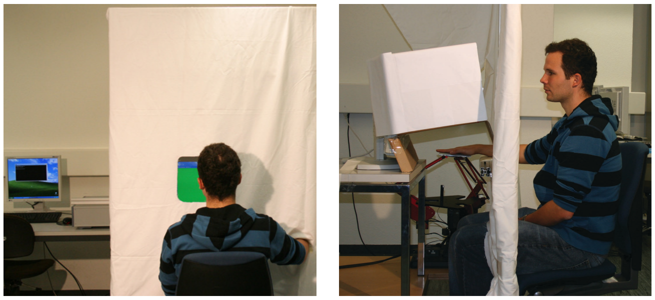
As seen in (7), σ_{22} is non-zero. The presence of normal stress, σ_{22}, and the inequality, $\sigma_{11} \neq \sigma_{22}$ is a manifestation of the "Poynting effect", and is a result of the material nonlinearity. In contrast, for a homogenous and isotropic body undergoing simple shear, the stress based on linear elasticity is

$$\sigma_{12} = G\kappa, \quad (8)$$

where G is the shear modulus, and all other components of stress are zero. (8) presents a computationally simple and easy to implement formulation, but such models do not exhibit the Poynting effect.

3 General Experimental Setup

In order to study the effects of shear and normal forces two degrees of freedom are needed. We choose to use the three-degree-of-freedom version of the Delta haptic device (Force Dimension, Lausanne, Switzerland) since it is designed to provide high-fidelity force-feedback over a large range of forces and also has a large workspace. As shown in Figure 1, the end-effector of the Delta haptic device was replaced by a custom-built flat plate covered with silicone rubber, representing the surface of the deformable virtual



(a) Front view. (b) Side view.

Figure 3: Experimental setup used for psychophysical experiments.

sample. The complete experimental setup is shown in Figure 3. Participants did not have direct visual access to the device, in order to prevent visual cues which might alter the force perception judgement.

Research participants were comfortably seated in front of the setup with their right forearm resting on a support to avoid fatigue. The test conductor was located to the left of the participant, away from direct view.

Participants were asked to place their palm on the flat plate and move the device slowly forward. Special care was taken that all subjects touched the plate in a similar fashion. For example, participants were not allowed to grasp the plate. After moving the plate forward by 12 cm, the computer display changed from green to red. Participants were told that this visual signal marked the end of their active movement. Following the forward shearing motion, haptic feedback was provided to guide a participant back to the initial starting position. This was done to ensure that all participants start the shearing task at the same position and shear the virtual model by the same amount. As participants performed the shearing motion, either shear or a combination of shear and normal forces were displayed to them.

The main target of this work is the multidimensional scaling analysis. However, in order to select the force samples to be presented in this main study, a pre-study was carried out focusing on force discrimination. The details of both experiments are provided in the following sections.

4 Force Discrimination Pre-Study

4.1 Methods

The main target of this experiment was to guide the selection of combinations of material parameters to be used in the MDS study. The pre-study was essentially a force discrimination test following a two-alternative, forced-choice (2AFC) design. Participants were instructed to shear the flat plate in the forward direction twice. They were informed that in addition to a shearing force, a normal force would be rendered during one of the two tasks. The participants were asked to provide feedback as to which trial included the normal force.

In the experiment, 4 male and 3 female participants took part, with a mean age of 26.4 years. None of the participants had any prior experience interacting with a haptic device. All participants were given about 15 minutes of practice time to familiarize themselves with the experiment. The duration of the session including instructions and breaks was three hours. Each participant was compensated with 40 CHF for taking part in the study. After the experiment, users provided additional feedback via a questionaire.

The rendered shear and normal forces were generated based on the stress equations of the Mooney-Rivlin model given in (6) and (7), respectively. Three different model categories with $C_1 = 100$ Pa$, C_1 = 200$ Pa, and $C_1 = 400$ Pa, and 10 different ratios of $\frac{C_2}{C_1}$ were chosen to yield 30 distinct virtual models. Table 1 provides an overview of the model parameters. Lower values of C_2 result in smaller normal forces. The material properties used in the pre-study are representative of liver and kidney soft tissues, as reported in [12].

Table 1: Parameters of virtual models used for force discrimination study. Shaded rows represent models that were used for the similarity rating study.

	Category I: $C_1 = 100$ Pa		Category II: $C_1 = 200$ Pa		Category III: $C_1 = 400$ Pa	
Model	$\frac{C_2}{C_1}$	C_2 (Pa)	$\frac{C_2}{C_1}$	C_2 (Pa)	$\frac{C_2}{C_1}$	C_2 (Pa)
a	0.005	0.5	0.05	10.0	0.05	20.0
b	0.01	1.0	0.1	20.0	0.15	60.0
c	0.05	5.0	0.15	30.0	0.25	100.0
d	0.1	10.0	0.2	40.0	0.35	140.0
e	0.2	20.0	0.3	60.0	0.45	180.0
f	0.3	30.0	0.4	80.0	0.55	220.0
g	0.4	40.0	0.5	100.0	0.65	260.0
h	0.5	50.0	0.6	120.0	0.75	300.0
i	0.6	60.0	0.8	160.0	1.0	400.0
j	0.75	75.0	0.9	180.0	1.25	500.0

For each of the trials, two forces were generated. One contained shear and normal forces according to a unique ratio of $\frac{C_2}{C_1}$, while in the other only the shear force was produced by setting $C_2 = 0$. Each of the reference virtual models was repeatedly shown 15 times in the pairwise comparisons, which resulted in a total to 450 trials per participant.

4.2 Results

The 2AFC data of the experiment were used to generate psychometric functions. The main focus is on the number of times participants were able to correctly identify the model with the normal forces. Curves were fitted using psignifit version 2.5.6 (http://bootstrap-software.org/psignifit/), a software package that implements the maximum-likelihood method [24].

For each participant, three psychometric functions were generated seperately for each of the three model categories. Figure 4 depicts an example curve for Category I ($C_1 = 100$ Pa). The *stimulus* is given by the ratio $\frac{C_2}{C_1}$, while the *performance* denotes the normalized ratio of correct detection of models containing normal forces.

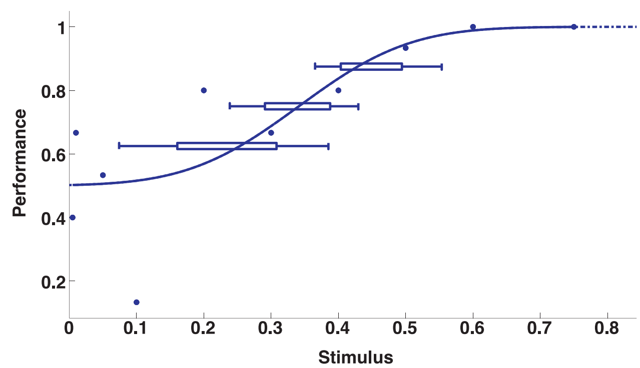


Figure 4: Psychometric curve for a research participant interacting with a Model I ($C_1 = 100$ Pa). *Stimulus* is the ratio $\frac{C_2}{C_1}$, while the *performance* denotes the normalized ratio of correct detection of models containing normal forces.

Point of subjective equality (PSEs) for the ratios $\frac{C_2}{C_1}$ were determined for all curves. The observed variations in the PSEs were found to be considerably large. Means and standard deviations were 0.27 ($\sigma = 0.23$) for Category I, 0.13 ($\sigma = 0.05$) for Category II, and 0.46 ($\sigma = 0.47$) for Category III. Large standard deviations indicate that participants found the task difficult. Especially for virtual models requiring display of large forces (mainly in Category III), the psychometric functions were distorted. In these cases, participants were not able to reliably identify models with normal forces.

These difficulties also became apparent in the written feedback given by the participants via the questionaires. For larger forces, 4 out of 7 participants reported problems in making their judgements. Participants also indicated that they experienced discontinuities due to the unstable rendering of large forces. Some participants also stated a low comfort level with using the setup.

The intended purpose of the pre-study was to support the selection of a subset of models that would be used in the similarity rating study. Models were chosen in such a way as to cover stiumulus ranges where participants had low, intermediate, and high performance values of correct discrimination of the normal forces. However, due to the reported problems in the study, our choice was finally guided only by a subset of participants who performed better in the pre-study. These models are highlighted in grey in Table 1.

5 Multidimensional Scaling Study

5.1 Methods

MDS is an analysis technique that provides information about relationships between a set of stimuli via similarity or dissimilarity ratings.

As in the pre-study, participants were asked to perform trials consisting of shearing two virtual deformable models with the device. The similarity between the forces felt should then be rated by the participants on a scale of 1 to 7, with 1 being most dissimilar and 7 most similar.

Table 2: Models used for the similarity rating study with mean PSE values obtained from force discrimination pre-study.

Model #	C_1 (Pa)	C_2 (Pa)	$\frac{C_2}{C_1}$	PSE
1	100	0.5	0.005	
2	100	20	0.2	0.27
3	100	75	0.75	
4	200	10	0.05	
5	200	60	0.3	0.13
6	200	180	0.9	
7	400	20	0.05	
8	400	180	0.45	0.46
9	400	500	1.25	

Shear and normal forces were presented according to the previously selected combinations of the parameters C_1 and C_2, representing nine different virtual tissue samples. Table 2 lists the used parameter sets. Each possible combination of models was presented 8 times, which resulted in a total of 360 unique pairwise comparisons.

The study had 8 participants, with equal number of males and females. The mean age of the participants was 28.1 years. The duration of one session including instructions and breaks was three-and-a-half hours; each participant was compensated with 40 CHF. The participants in this study were not the same as in the pre-study, in order to avoid learning effects. Again, questionnaires were provided to the participants at the end of the study. In these, the participants were asked to describe the virtual models and explain the cues they used to perform the similarity rating.

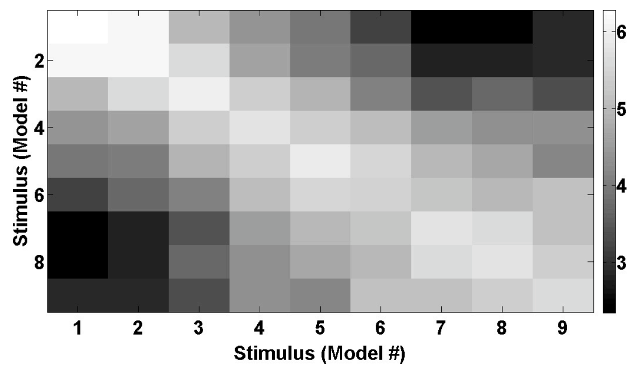


Figure 5: Visual representation of similarity rating matrix for all participants. The values correspond to mean rating values of all participants.

5.2 MDS Analysis

The input to the MDS analysis were the similarity ratings of the pairs of rendered forces; the output was a map of these renderings in a psychological space which helps us to interpret the similarity data.

Figure 5 provides a visual representation of the mean similarity ratings of all participants. The lighter color signifies that participants perceived the two models as being similar, and dark color represents dissimilarity between two models. Based on this proximity map an MDS analysis was performed using PROXSCAL (Proximity Scaling) as implemented in SPSS (SPSS Inc., Chicago, USA).

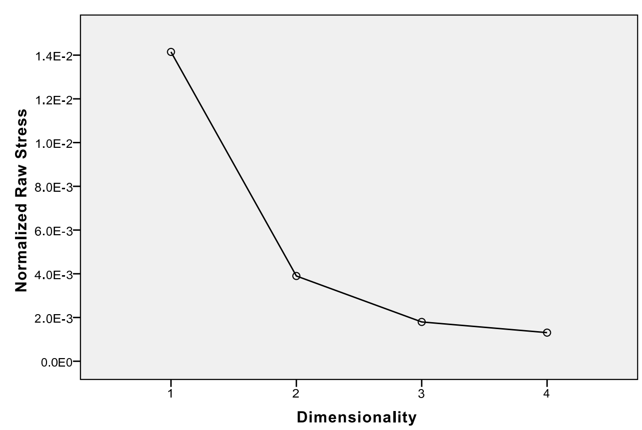
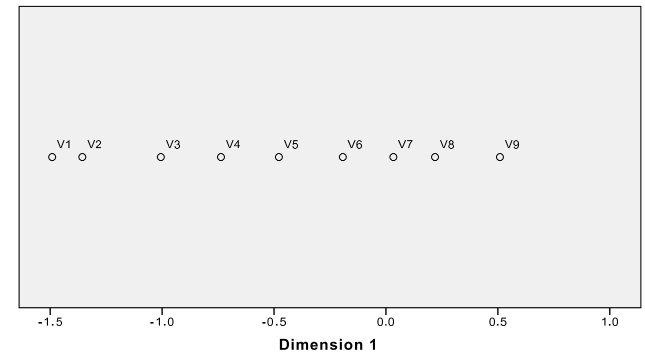


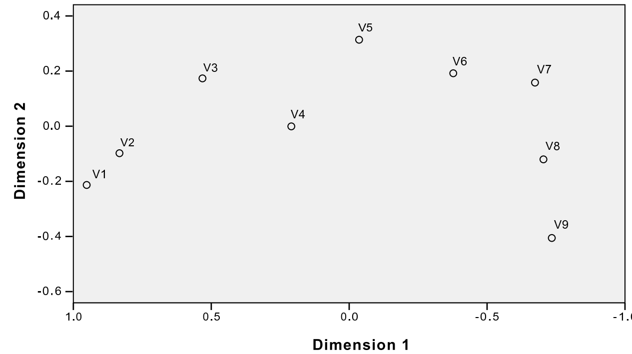
Figure 6: Scree plot of MDS analysis showing goodness-of- t for various dimensions.

The first question to be addressed by the results of the analysis was the appropriate dimensionality of the output configuration. This can be determined by inspection of the elbow in the scree plot obtained from the analysis. Figure 6 shows the scree plot for MDS solutions (stress functions) with increasing dimensionality. As indicated by the elbow in the curve, two perceptual dimensions provide a better fit of the data than only using one dimension.

An MDS analysis does not provide labels for the dimensions of the output configurations. These must be obtained by visual inspection of the output configuration and interpretation of the feedback given by the participants. Therefore, in the next step we exam-



(a) Configuration with one dimension.



(b) Configuration with two dimensions.

Figure 7: Dimensional con gurations obtained from MDS analysis.

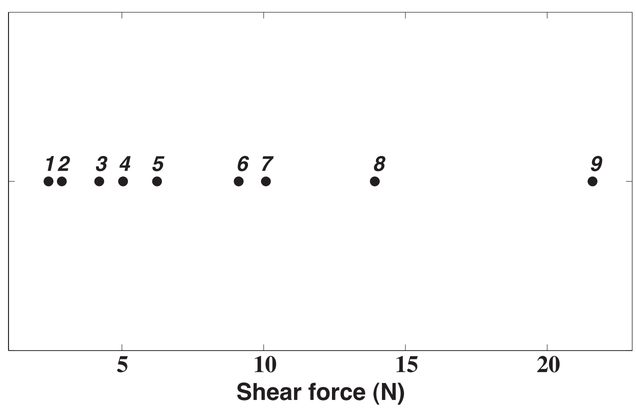


Figure 8: One-dimensional arrangement of samples according to their shear force.

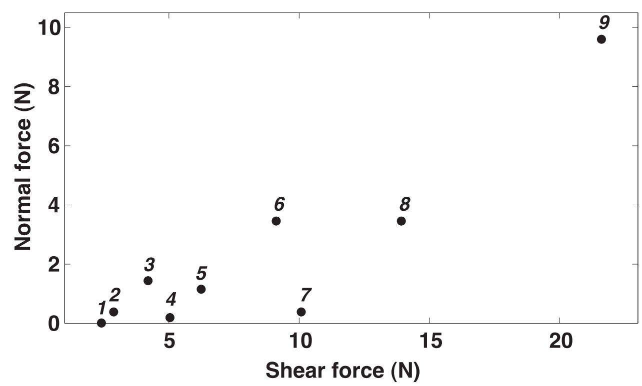


Figure 9: Normal versus shear forces for the various models used in the MDS study.

ine the output configurations of the one- and two-dimensional solutions.

Figure 7 shows the configurations obtained both for one and two dimensions in perceptual space. Closer inspection of the one-dimensional configuration (Figure 7(a)) indicates an ordering of the samples according to the corresponding shear force of each sample. For comparison, the shear forces rendered with the samples are depicted in one dimension in Figure 8. As observed, the MDS appears to be successful in recovering the ordering of the samples according to the shear force magnitude. However, the distances between the samples were not appropriately reproduced. Nevertheless, the first dimension recovered from the similarity data likely represents the shear force of the samples.

In the two-dimensional configuration (Figure 7(b)), the interpretation of the dimensions is less straight-forward. However, following the discussion in the case of one dimension, it makes sense to consider for the two-dimensional configuration the normal forces in addition to the shear forces rendered for the samples. Therefore, the corresponding forces are plotted for all virtual models in Figure 9.

The resulting MDS arrangement in two-dimensional perceptual space has similarities in the first five samples of the force plot. For samples with larger forces, distortions skew the two-dimensional configuration. Thus, similar to the pre-study, participants seemed to have problems perceiving normal components for renderings with high force magnitudes. Similar findings were again obtained from the questionnaires which are discussed below.

According to the questionnaire, participants assumed on average that eight different virtual models were presented, which is close to the actual number of nine examined samples. The models were generally likened to “play-doh”, “rubber”, “cake”, “jelly”, or “sponge”. Materials of varying stiffness generate different forces when palpated. Further, participants would probably have not expected to feel any normal forces when palpating objects like “jelly”, “sponge”, etc., and the perceived reaction along the shearing direction could have been interpreted as overall object stiffness. Thus, the labeling in Figures 7(a) and 8 supports the interpretation of the first dimension of the MDS configuration to be related to shear forces.

Participants generally reported difficulties in judging the similarities between the models. Also, 5 out of 8 participants reported problems in their ratings due to forces when the forces became large. It was also stated that in the case of large forces, moving the device felt discontinuous and awkward. This was due to device instabilities during rendering of large forces. This could be an explanation for the deviation of the higher force samples in the perceptual space.

6 Conclusions and Future Work

The presence of normal forces during shearing of tissue is a consequence of the nonlinearity of the material, which is not observed in linear elastic or non-physical models. For isotropic materials, this phenomenon is known as the Poynting effect. An MDS study was performed to investigate the influence of the Poynting effect on user perception.

Participants interacted with virtual nonlinear elastic tissue models via the Delta haptic device. The selection of the material parameters of the samples was based on a 2AFC force discrimination pre-study. Following the pre-study, MDS was performed on similarity ratings obtained by comparing nine different virtual models. The first and second dimensions recovered from the similarity data represented the shear and normal forces, respectively, showing that humans perceived both forces during the task. The MDS arrangement in two-dimensional perceptual space was valid for small resultant forces.

For both the force discrimination pre-study and the MDS study, participants had difficulty perceiving normal components for rendering with high force magnitudes (models 6 through 9). These problems were associated with limitations in rendering large forces by the device and normal forces being masked when shear components were large. To test large forces, the experimental setup should be redesigned in the future. This could be accomplished by using a real-time operating system coupled to the Delta haptic device and also increasing the sampling frequency to speed up force rendering. The addition of virtual or mechanical damping might also mitigate some of the observed instabilities. The study design could also be changed so that participants perform smaller shearing motions, which in turn would prevent larger forces from being rendered. Also, instead of using a virtual model, the participants could interact with physical biological and artificial tissue samples. This would produce realistic shear and normal forces. An increase in the number of participants in the research study would improve statistical significance of the results.

The long-term goal of this research is to quantify and understand how organ model fidelity affects realism in surgical simulators and planners. Considering physical phenomena such as the Poynting effect, which is significant for some organs but may not be for others, in combination with human perception studies, will allow researchers to make justified simplifications to create realistic, real-time simulation of realistic tool-tissue interactions.

Acknowledgements

The authors wish to thank Raphael Hoever (ETH Zürich) for helping with the experimental setup. This work was supported by the Link Foundation Fellowship, IEEE RAS Technical Committee on Haptics Student Exchange Travel Award, and Swiss National Science Foundation via the NCCR on Computer Aided and Image Guided Medical Interventions.

References

[1] C. Basdogan, M. Sedef, M. Harders, and S. Wesarg. VR-based simulators for training in minimally invasive surgery. *IEEE Computer Graphics and Applications*, 27(2):54–66, 2007.

[2] W. M. Bergmann Tiest and A. M. L. Kappers. Analysis of haptic perception of materials by multidimensional scaling and physical measurements of roughness and compressibility. *Acta Psychologica*, 121(1):1–20, 2006.

[3] T. F. Cox and M. A. Cox. *Multidimensional scaling*. CRC Press LLC, Boca Raton, USA, second edition, 2001.

[4] E. Dehghan and S. E. Salcudean. Comparison of linear and mon-linear models in 2d needle insertion simulation. In *Computational Biomechanics for Medicine:9th MICCAI Conf. Workshop*, October 2006.

[5] N. Dhruv and F. Tendick. Frequency dependence of complience contrast detection. *ASME J. Dynamic Systems, Measurement, and Control*, 2(1):1087–1093, 2000.

[6] B. Forsyth and K. E. MacLean. Predictive haptic guidance: intelligent user assistance for the control of dynamic tasks. *IEEE Trans. Visualization and Computer Graphics*, 12(1):103–113, 2006.

[7] Y. C. Fung. *Biomechanics: mechanical properties of living tissues*. Springer-Verlag Inc., New York, USA, second edition, 1993.

[8] S. F. F. Gibson and B. Mirtich. A survey of deformable modeling in computer graphics. Technical Report TR97-19, Mitsubishi Electric Research Laboratories, November 1997.

[9] M. E. Gurtin. *An introduction to continuum mechanics*. Academic Press, London, UK, first edition, 2003.

[10] M. Hollins, R. Faldowski, S. Rao, and F. Young. Individual differences in perceptual space for tactile textures: evidence from multidimensional scaling analysis. *Perception and Psychophysics*, 54(6):697–705, 1993.

[11] L. A. Jones. Perception and control of finger forces. In *Proc. ASME Dynamic Systems and Control Division*, volume 64, pages 133–137, Anaheim, USA, November 1998.

[12] H. Kim and M. Srinivasan. Characterization of viscoelastic soft tissue properties from in vivo animal experiments and inverse fe parameter estimation. In *8th Int l Conf. on Medical Image Computing and Computer Assisted Intervention*, volume 3750 of *Lecture Notes in Computer Science*, pages 599–606. Springer, Berlin / Heidelberg, 2005.

[13] R. L. Klatzky, S. Lederman, and C. Reed. Haptic integration of object properties: texture, hardness, and planar contour. *Journal of Experimental Psychology: Human Perception and Performance*, 15(1):45–57, 1989.

[14] S. J. Lederman. The perception of surface roughness by active and passive touch. *Bulletin of the Psychonomic Soceity*, 18(5):253–255, 1981.

[15] P. Leskovsky, T. Cooke, M. Ernst, and M. Harders. Using multidimensional scaling to quantify the fidelity of haptic rendering of deformable objects. In *Proc. Eurohaptics*, volume 1, pages 289–295, Paris, France, March 2006.

[16] A. Liu, F. Tendick, K. Cleary, and C. Kaufmann. A survey of surgical simulation: applications, technology, and education. *Presence: Teleoperators & Virtual Environments*, 12(6):599–614, 2003.

[17] K. E. MacLean and M. J. Enriquez. Perceptual design of haptic icons. In *EuroHaptics Conference*, volume 1, pages 1–13, Dublin, UK, July 2003.

[18] S. Misra, A. M. Okamura, and K. T. Ramesh. Force feedback is noticeably different for linear versus nonlinear elastic tissue models. In *2nd Joint EuroHaptics Conf. and Symp. on Haptic Interfaces for Virtual Environment and Teleoperator Systems - World Haptics*, volume 1, pages 519–524, Tsukuba, Japan, March 2007.

[19] S. Misra, K. T. Ramesh, and A. M. Okamura. Modeling of tool-tissue interactions for computer-based surgical simulation: a literature review. *Presence: Teleoperators & Virtual Environments*, 17(5):463–491, 2008.

[20] S. Misra, K. T. Ramesh, and A. M. Okamura. Physically valid surgical simulators: linear versus nonlinear tissue models. In *Studies in Health Technology and Informatics - Medicine Meets Virtual Reality*, volume 1, pages 293–295, Long Beach, USA, January 2008.

[21] J. Pasquero, J. Luk, S. Little, and K. E. MacLean. Perception analysis of haptic icons: an investigation into the validity of cluster sorted mds. In *Proc. 14th Symp. on Haptic Interfaces for Virtual Environments and Teleoperator Systems*, volume 1, pages 437–444, Washington D.C., USA, March 2006.

[22] E. Ruffaldi, D. Morris, T. Edmunds, F. Barbagli, and D. K. Pai. Standardized evaluation of haptic rendering systems. In *Proc. 14th Symp. on Haptic Interfaces for Virtual Environments and Teleoperator Systems*, volume 1, pages 225–232, Washington D.C., USA, March 2006.

[23] H. Z. Tan, M. A. Srinivasan, B. Eberman, and B. Cheng. Human factors for the design of force-reflecting haptic interfaces. In *Proc. 3rd Int l. Symp. on Haptic Interfaces for Virtual Environment and Teleoperator Systems (ASME/ASME Dynamic Systems and Control Division)*, volume 55, pages 353–359, Chicago, USA, March 1994.

[24] F. A. Wichmann and N. J. Hill. The psychometric function: I. fitting, sampling and goodness-of-fit. *Perception and Psychophysics*, 63(8):1293–1313, 2001.

[25] M. Yoshida. Dimensions of tactual impressions (1). *Japanese Psychological Research*, 10(3):123–137, 1968.

[26] M. Yoshida. Dimensions of tactual impressions (2). *Japanese Psychological Research*, 10(4):157–173, 1968.