# Data-Driven Representation of Soft Deformable Objects Based on Force-Torque Data and 3D Vision Measurements

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# Introduction

- The acquisition and realistic representation of soft objects deformations is still an active area of research.

- Realistic, plausible models require the acquisition of experimental measurements using physical interaction with the object in order to capture its complex behavior when subject to various forces.

- Tests are carried out based on instrumented indentation tests and usually involve:

  - the monitoring of the evolution of the force (e.g. its magnitude, direction, and location) applied by a force sensor

  - a visual capture of the deformed object surface to collect geometry data.

# Proposed Framework for Soft Object Deformation Representation

- A data-driven neural-network-based model is proposed for capturing implicitly deformations of a soft object, without requiring any knowledge on the object material.

- A novel approach advantageously combining distance-based clustering, stratified sampling and neural gas-tuned mesh simplification is proposed to describe the particularities of the deformation.

- The representation is denser in the region of the deformation while still preserving the object overall shape and only using a low percentage of the number of vertices in the mesh.

# Proposed Framework for Soft Object Deformation Representation

- Data Acquisition

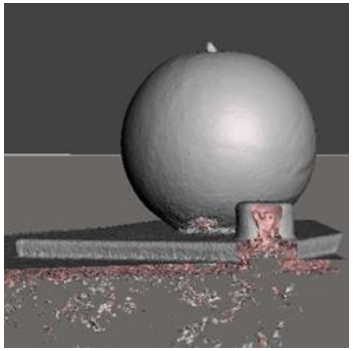

Acquisition platform for soft object deformation behavior including a Kinect sensor to collect 3D geometry data and an ATI force-torque sensor to measure the force magnitude;

# Proposed Framework for Soft Object Deformation Representation

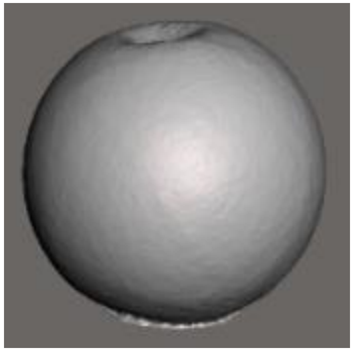
- Data Preparation
  - A synchronization process is required to associate the correct surface deformation with the corresponding angle and force magnitude measurements.
  - The deformed object model is considered to be the result of:
    - The application of a force with a magnitude equal to the average magnitude of forces collected over the time it takes for the 3D model to be collected
      - $F_{Pa} = \sum_{t=t_1}^{t_2} F_P / n$, where $n$ is the number of readings returned by the sensor in the interval $t_1 - t_2$,
      - $F_P = \sqrt{F_x^2 + F_y^2 + F_z^2}$
      - $t_1 - t_2$ is the time interval it takes for the 3D model to be collected with the Kinect
    - The force is considered to be applied at an angle equal to the average of angle values extracted from images of the platform (collected each 10 seconds) over the time it takes for the 3D model to be collected.
      - $a_{Pa} = \sum_{t=t_1}^{t_2} a_P / m$, where $m$ is the number of images captured in the interval $t_1 - t_2$.

# Proposed Framework for Soft Object Deformation Representation

- Data Preparation
  - The undesired elements in the model (i.e. the table on which the object is placed, the fixed landmarks required by the software to merge data from multiple viewpoints and the probing tip) are removed in part automatically, in part manually.



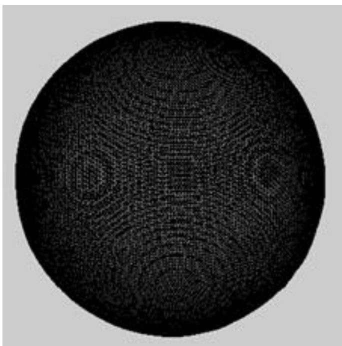
raw data collected



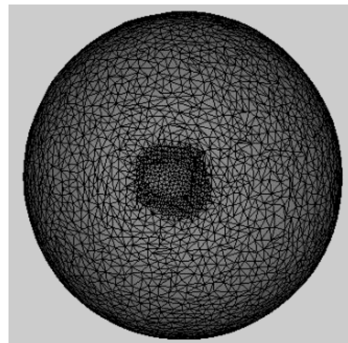
cleaned object model

# Proposed Framework for Soft Object Deformation Representation

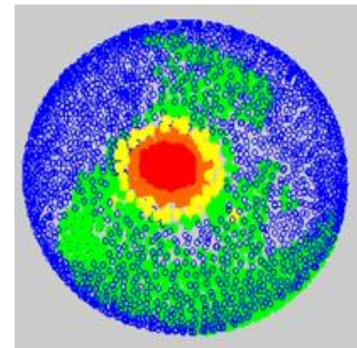
- Deformation Characterization Steps



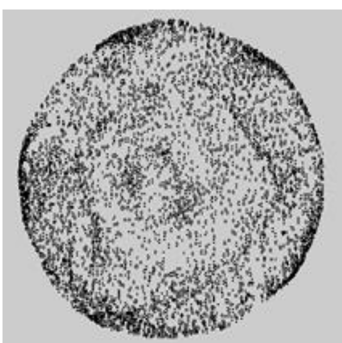
initial object mesh



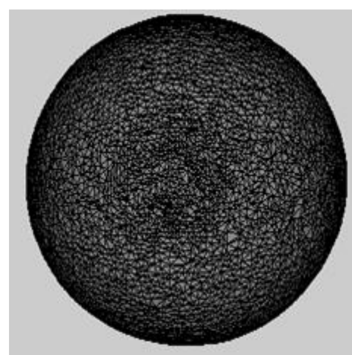
mesh with higher density in the deformed area



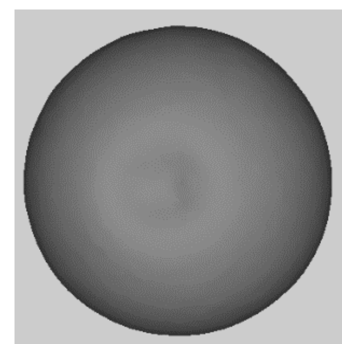
stratified sampled data



neural-gas fitting



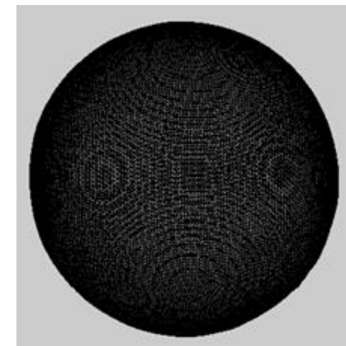
neural-gas-tuned simplification

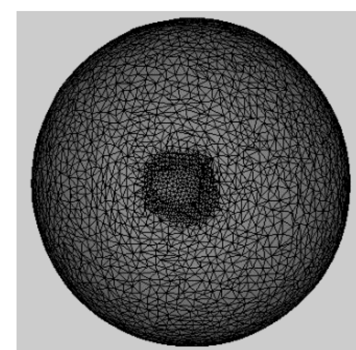


final object model

# Proposed Framework for Soft Object Deformation Representation

- Deformation Characterization
  - **Mesh with higher density in deformed area**
    - The QSlim[14] algorithm is adapted to only simplify points that are not the interaction point with the probing tip and its 12-degree immediate neighbors.
    - The value of 12 neighbors is chosen by trial and error (correctly captures the entire deformed area).
    - This process ensures a uniform representation of the object by defining an equal number of faces (30% of the faces in the initial model) for all the instances of a deformed object.
    - The 30% is obtained by monitoring the evolution of the errors and of the computation time for an increasing percentage and finding the best compromise between the two.



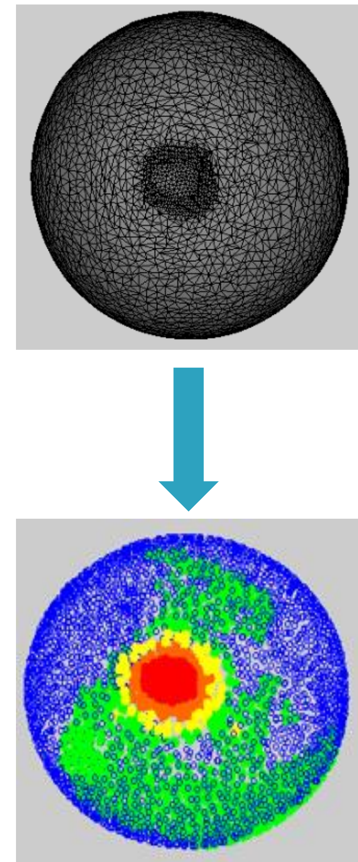


# Proposed Framework for Soft Object Deformation Representation

- Deformation Characterization
  - **Cluster Identification for Stratified Sampling**
    - A stratified sampling technique is employed to only retain a subset of data for neural-gas tuning.
    - The normalized interval between 0 and the maximum distance between the non-deformed mesh and each instance of the object under the study is gradually split in an increasing number of equal intervals (=number of clusters)
    - The points in the deformed area around the probing tip are compared with the cluster situated at the largest distance
      - it is desired that the highest possible number of points from the deformed zone is situated in this cluster.
    - A number of 5 clusters was identified to ensure the best results.

# Proposed Framework for Soft Object Deformation Representation

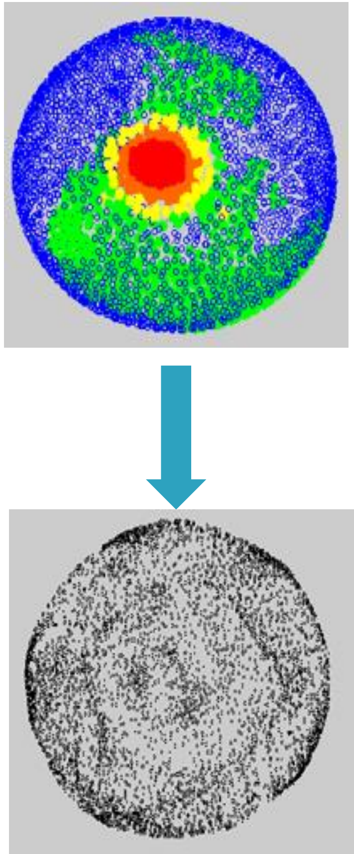
- Deformation Characterization
  - **Stratified Sampling**
    - Points are sampled randomly but in various proportions from each cluster to identify the adequate amount of data to be used by monitoring the evolution of errors.
    - The proportions are varied by taking into consideration the fact that a good representation is desired specifically in the deformed area
      - more samples are desired where the deformation is larger.
    - The adequate amount of data is identified by varying iteratively the percentage of data randomly extracted from each cluster from 25% to 90%
      - The best combination: 87% from the closest (red) cluster, 77%, 67%, 57%, respectively from the 2nd, 3rd, and 4th cluster, and 47% from the farthest distanced cluster points



blue=closest points
green, yellow, orange=increasingly more distant points
red = points at largest distance (deformed area)

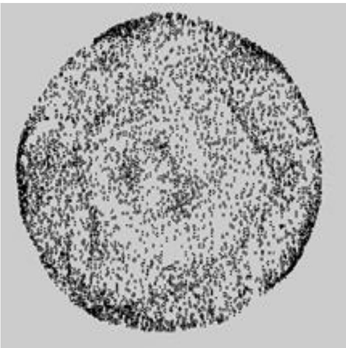
# Proposed Framework for Soft Object Deformation Representation

- Deformation Characterization
  - **Neural gas fitting**
    - A neural gas network is fitted over the stratified sampled data.
    - The choice of a neural gas network [15] is justified by the fact that it converges quickly, reaches a low distortion error and it can capture fine details [16].
    - The network takes the form of the object, while preserving more details in the regions where the local geometry changes [16].
    - Ensures that fine differences around the deformed zone and over the surface of the object can be captured accurately in the model.

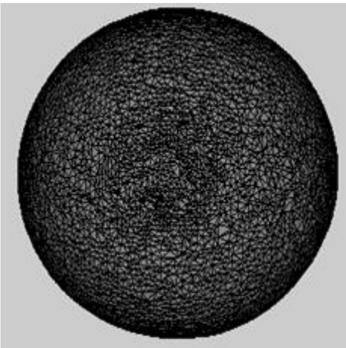


# Proposed Framework for Soft Object Deformation Representation

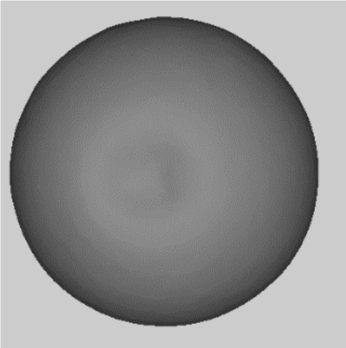
- Deformation Characterization
  - Neural Gas Tuned Simplification
    - Using the adapted QSlim algorithm, the areas identified by neural gas are kept at higher resolution in the simplification, by rearranging the triangles of the selectively-densified mesh



neural-gas fitting



neural-gas-tuned simplification



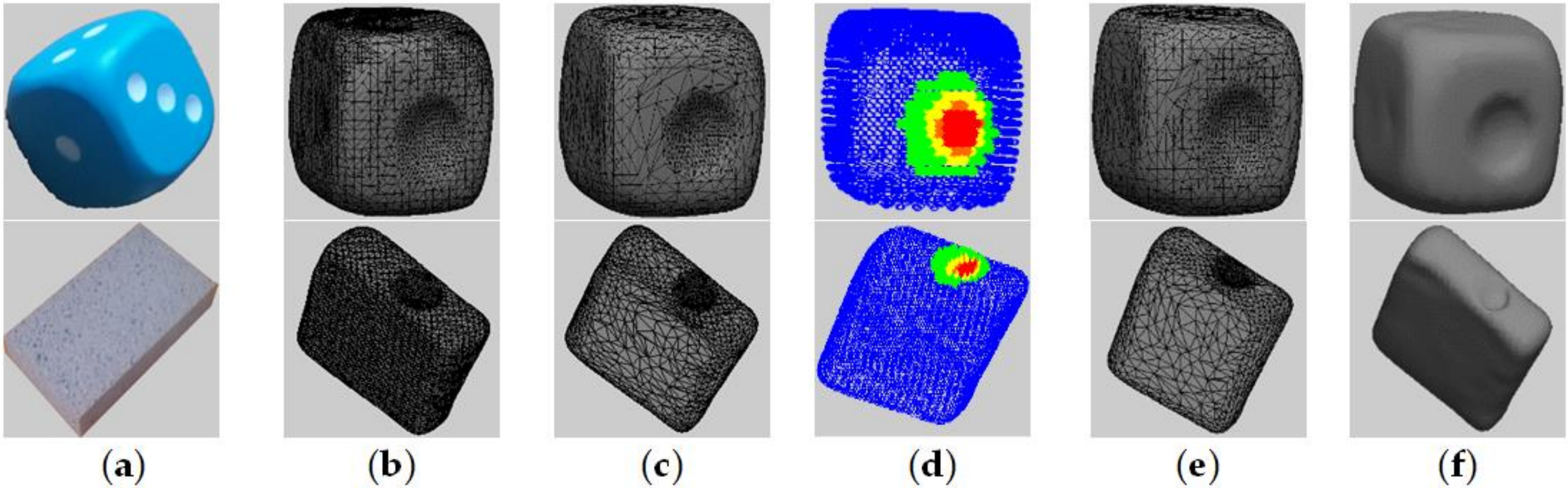
final object model

# Proposed Framework for Soft Object Deformation Representation

- Quantitative Evaluation
  - **Metro**
    - computes the Hausdorff distance
    - returns the maximum (max) and mean distance (mean) as well as the variance (rms) between the initial and the simplified mesh
  - **Perceptual error**
    - the normalized Laplacian pyramid-based image quality assessment error takes into account human perceptual quality judgments
    - images are collected over the simplified models of objects from 25 viewpoints and compared with the images of the full-resolution object from the same viewpoints
    - error measures for each instance of an object are reported as an average over these viewpoints

# Experimental Results

- Results for the cube and sponge:

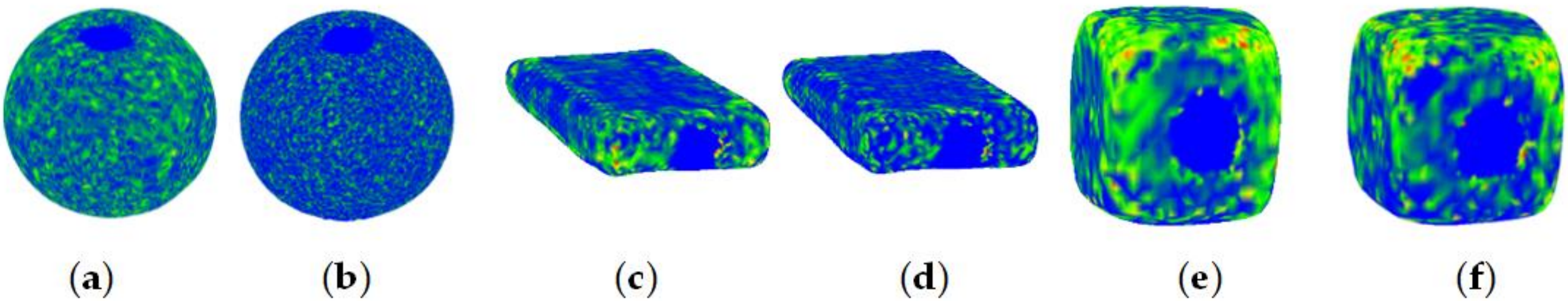



(a) initial object; (b) initial object mesh; (c) mesh with higher density in the deformed area; (d) stratified sampled data for neural-gas mapping; (e) neural-gas-tuned simplified object mesh and (f) final object model.

blue=closest points
green, yellow, orange=increasingly more distant points
red = points at largest distance (deformed area)

# Experimental Results

- Results for ball, cube and sponge:




(a) selectively-densified mesh around probing point for ball for $F_{Pa}$=4.5N, $a_{Pa}$=10º;
(b) final mesh for ball $F_{Pa}$=4.5N, $a_{Pa}$=10º;
(c) selectively-densified mesh around probing point for sponge for $F_{Pa}$=3.7N, $a_{Pa}$=49º;
(d) final mesh for sponge for $F_{Pa}$=3.7N, $a_{Pa}$=49º
(e) selectively-densified mesh around probing point for cube for $F_{Pa}$=5N, $a_{Pa}$=85º;
(f) final mesh for cube for $F_{Pa}$=5N, $a_{Pa}$=85º.

blue=perfect match
green, yellow, orange=increasingly higher error
red = highest error

# Experimental Results

- Quantitative Evaluation
  - The overall perceptual similarity achieved is on average:
    - 74% over the entire surface of the object
    - 91% over the deformed area;
  - The average computing time per object of 0.43s on a Pentium III, 2Ghz CPU, 64 bit operating system, 4Ghz memory machine

| | Metro overall error ($e^{-3}$) max/mean/rms | Perceptual overall error (similarity%) | Metro error in deformed area ($e^{-5}$) max/mean/rms | Perceptual error (similarity%) in deformed area | Computing time/object |
|---|---|---|---|---|---|
| Ball | 16.7/5.58/7.4 | 0.205 (79.5%) | 24.3/3.05/4.69 | 0.082 (91.8%) | 0.72s |
| Cube | 46.2/11.8/17.2 | 0.286 (71.4%) | 25.7/3.47/5.07 | 0.127 (87.3%) | 0.35s |
| Sponge | 21.6/5.09/7.55 | 0.281 (71.9%) | 22.4/2.29/3.51 | 0.070 (93.0%) | 0.23s |
| Average | **28.16/7.49/10.7** | **0.257 (74.3%)** | **24.13/2.93/4.42** | **0.093 (90.7%)** | **0.43s** |

# Conclusion

- The paper proposed an innovative data-driven representation of soft objects based on selectively-densified simplification, stratified sampling and neural gas tuning.

- The proposed solution avoids recuperating elasticity parameters which cannot be precisely and accurately identified for certain materials such as foam or rubber

- The proposed solution eliminates the need to make assumptions on the material, such as its homogeneity or isotropy, as often encountered in the literature.

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