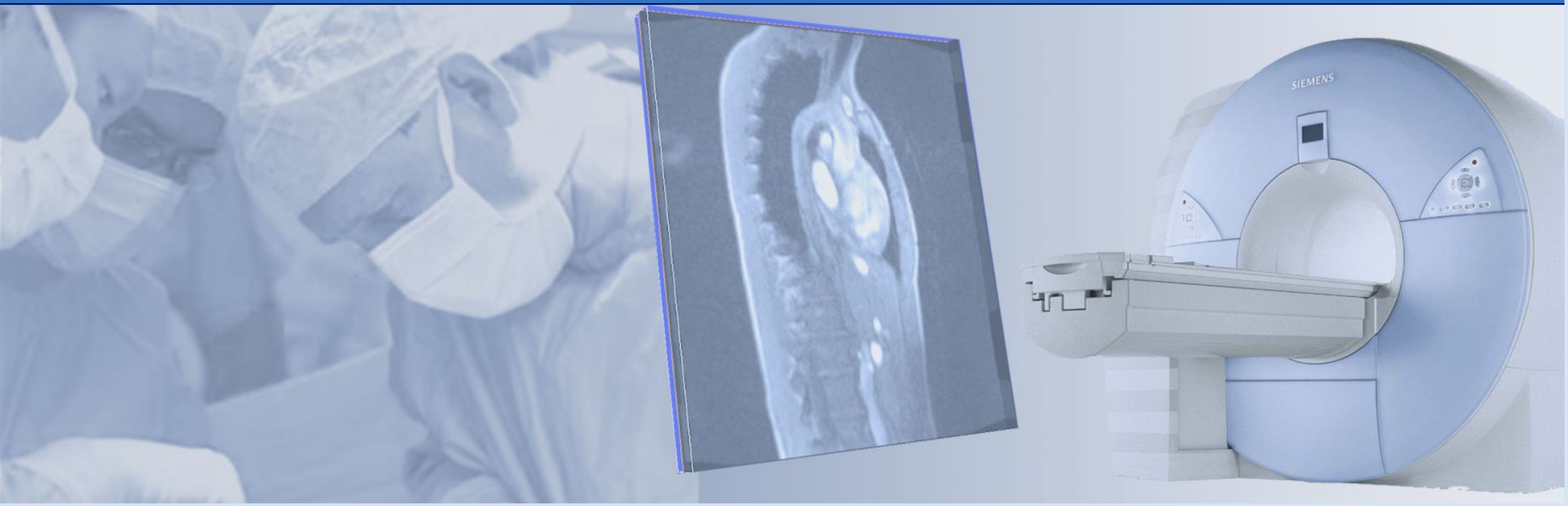
Computer- and robot-assisted Surgery



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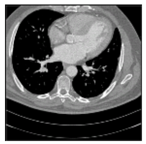
Universitätsklinikum Carl Gustav Carus Dresden
Medizinische Fakultät Carl Gustav Carus, TU Dresden
Helmholtz-Zentrum Dresden-Rossendorf

Lecture 11

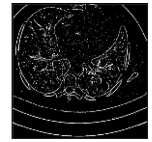
Surgical Workflow Analysis and Surgical Training

Process chain computer-assisted surgery

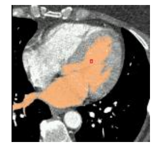
Image acquisition



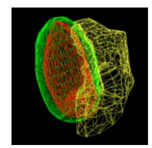
Pre-processing



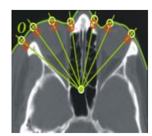
Segmentation



Modeling



Registration



Visualization/
Assistance

Overview of the lecture

- Surgical workflow analysis and training
  - Motivation
  - Tasks
  - Video analysis
    - HMMs
    - Recurrent Neural Networks
  - Training simulator
  - Simulating tissue behavior

Context-aware assistance

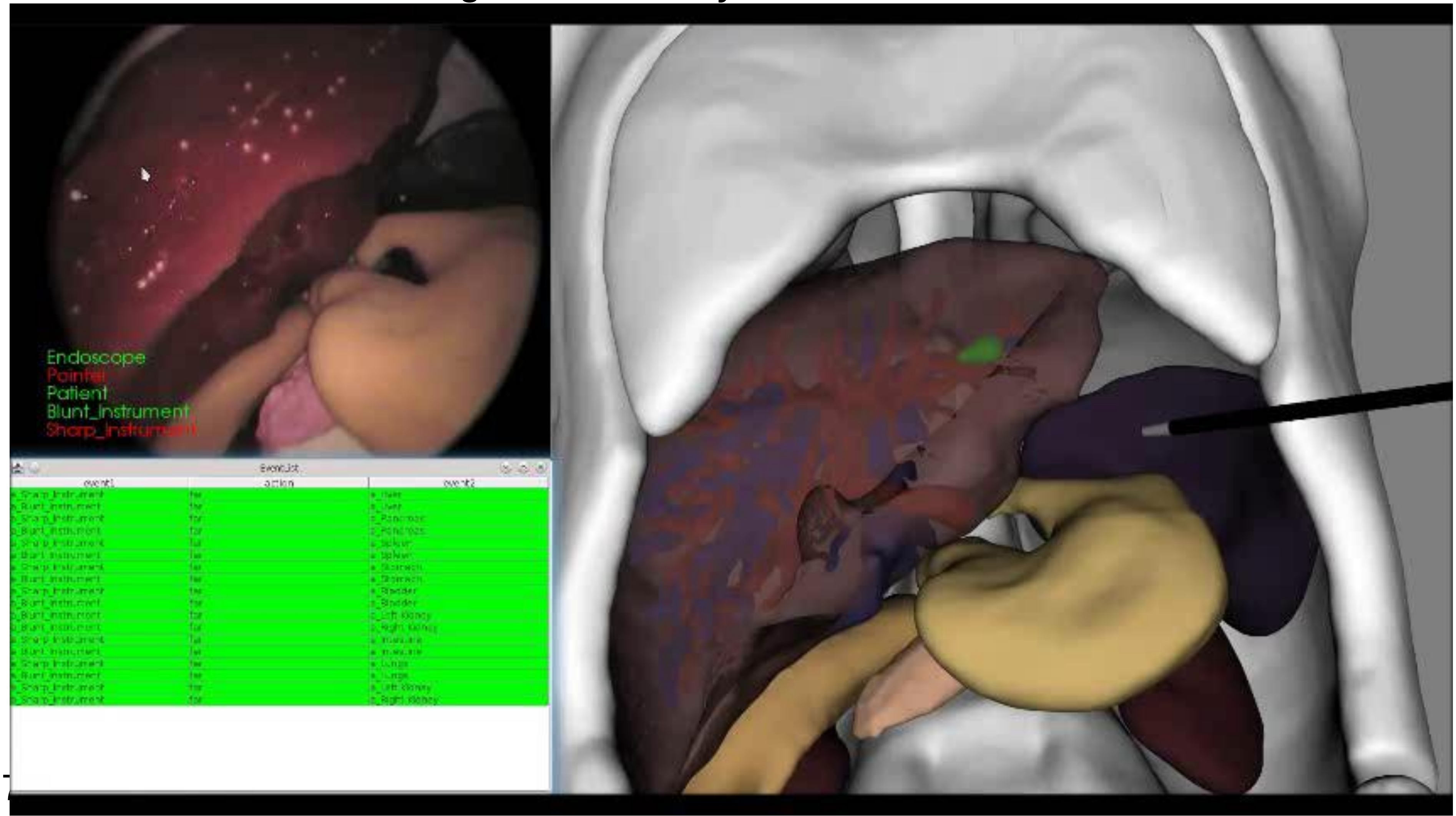
Context-aware assistance

Context-aware assistance

Context-aware assistance: provide the right assistance at the right time!

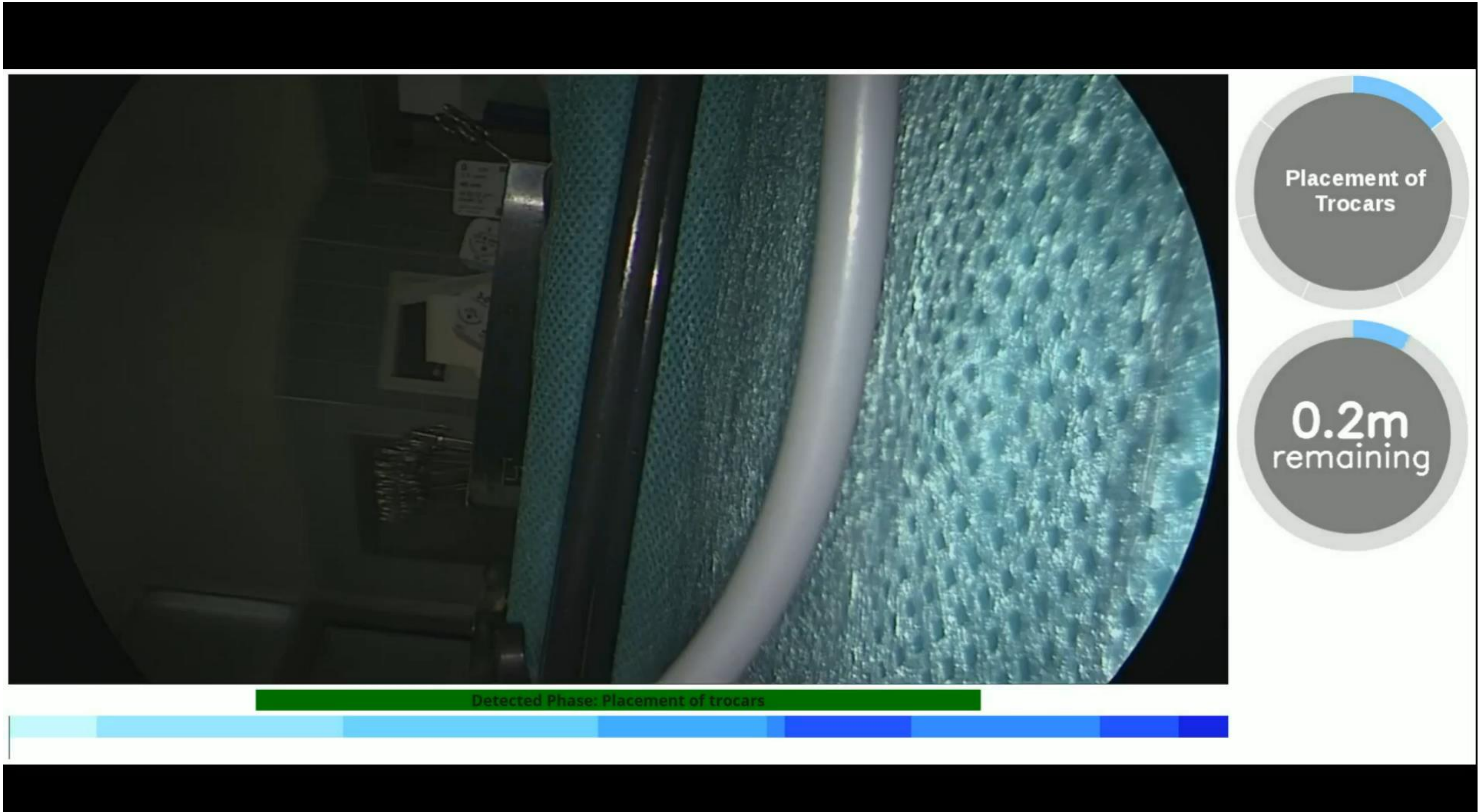
Motivation Surgical Workflow

- Context-aware augmented reality



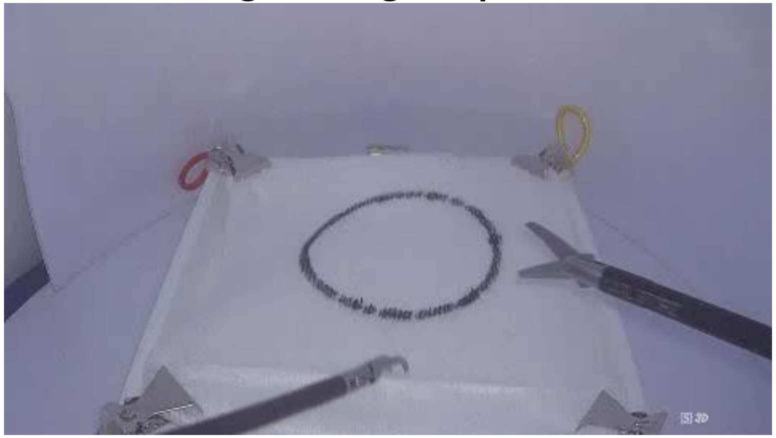
Motivation Surgical Workflow

- Predicting procedure duration



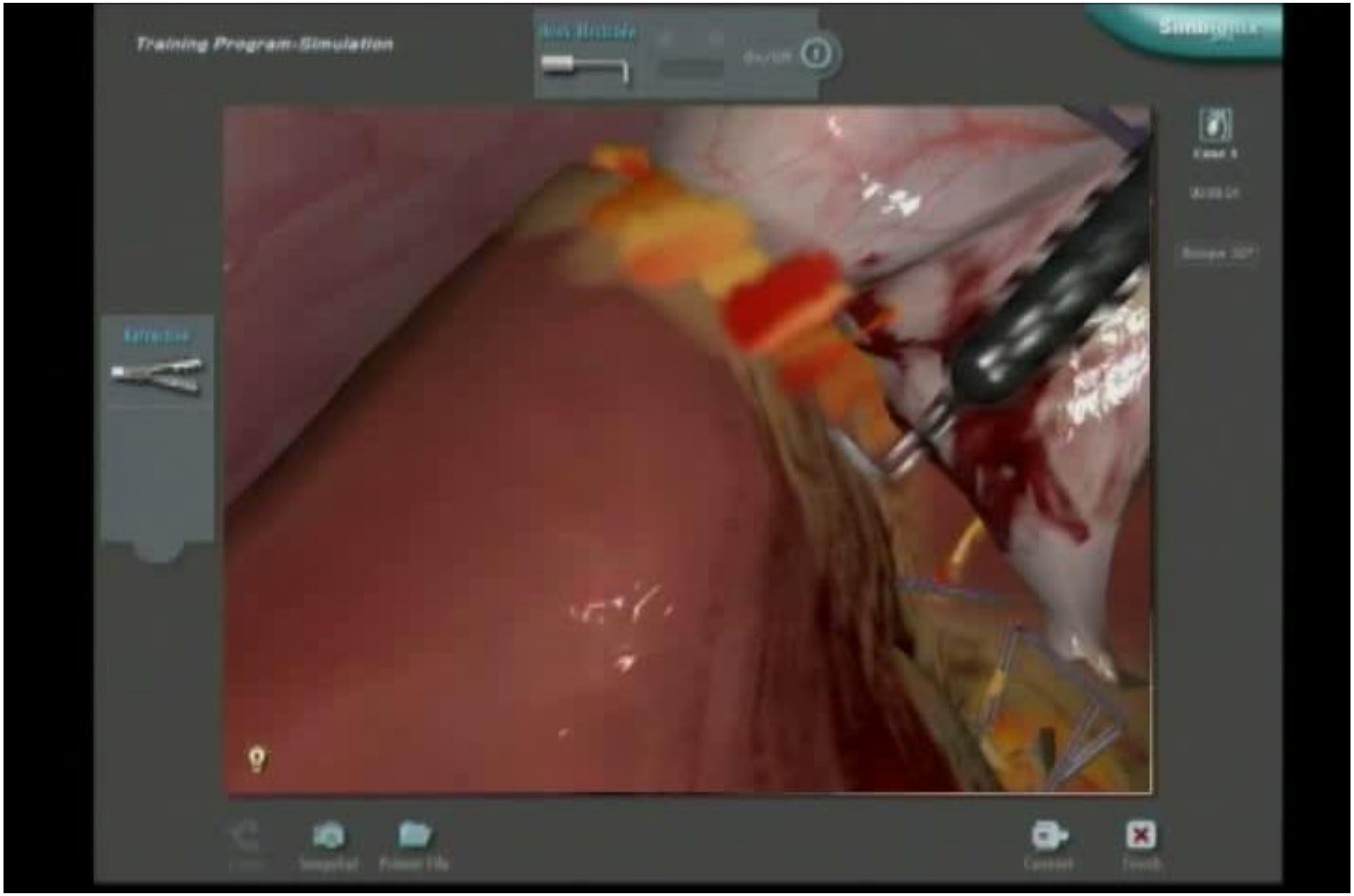
Motivation Surgical Training

- Training using expert models @ TSO



Motivation Surgical Training

- VR Trainer (LAP Mentor from Simbionix)



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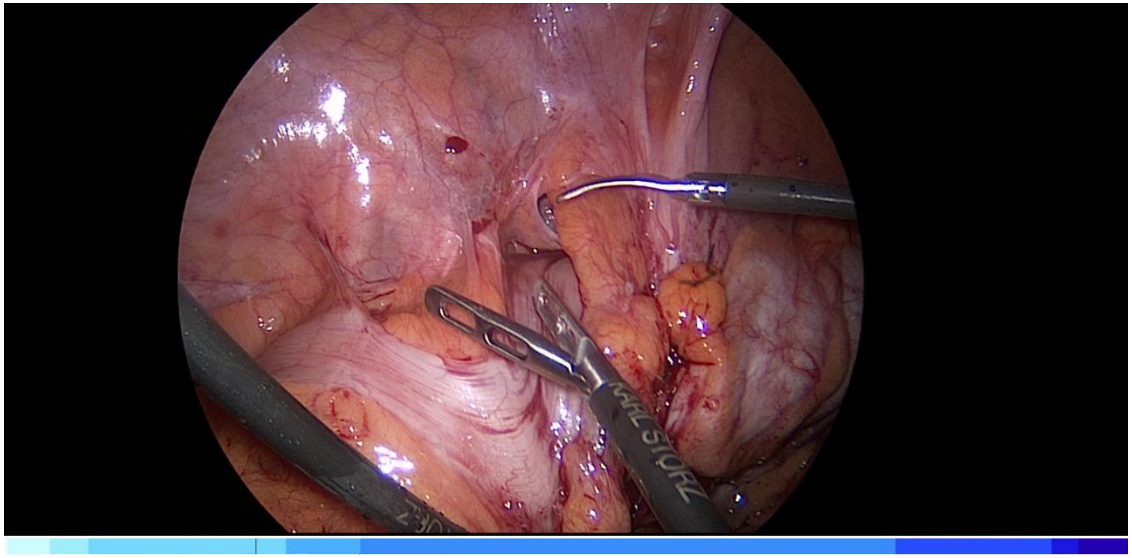
Workflow Analysis Tasks: Phase segmentation

- Divide operation into temporally connected segments
  - E.g. describing connected tasks
  - Can be used to guide assistance systems

- Example gallbladder removal surgery

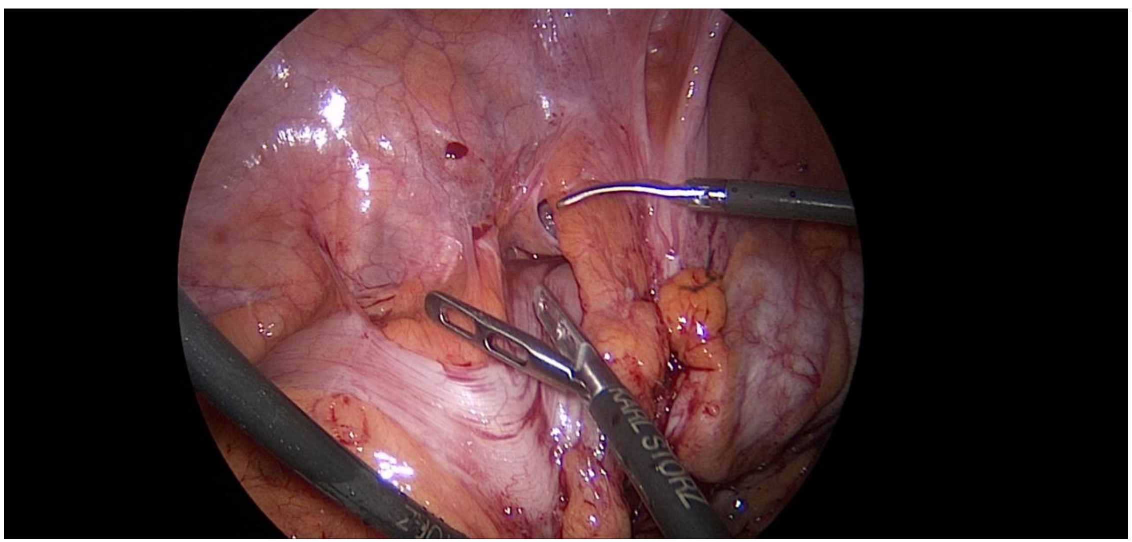


Phase name
Preparation
Calot triangle dissection
Clipping and cutting
Gallbladder dissection
Gallbladder packaging
Cleaning and coagulation
Gallbladder retraction

Workflow Analysis Tasks: Instrument presence

- Determine which instruments are currently visible/used
  - Progress of surgery
  - Can be used to guide assistance systems

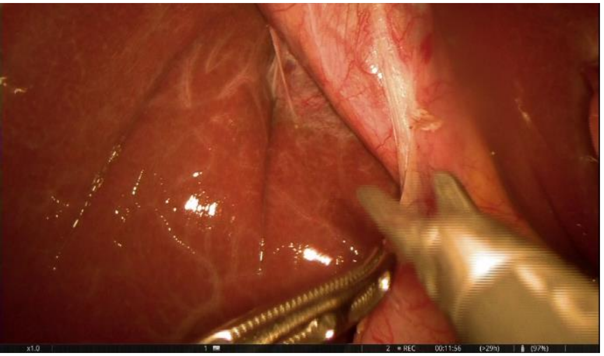
- Example gallbladder removal surgery



Tool category name
Grasper
Clipper
Coagulation instrument
Scissors
Suction/irrigation
Specimen bag
Stapler

Workflow Analysis Tasks: Action recognition

- Determine what the surgeon is performing currently
  - Progress of surgery
  - Can be used to guide assistance systems



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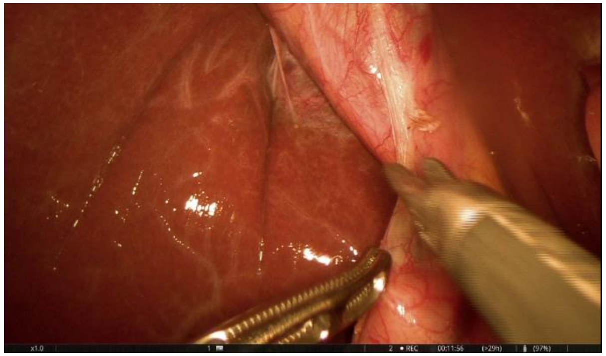

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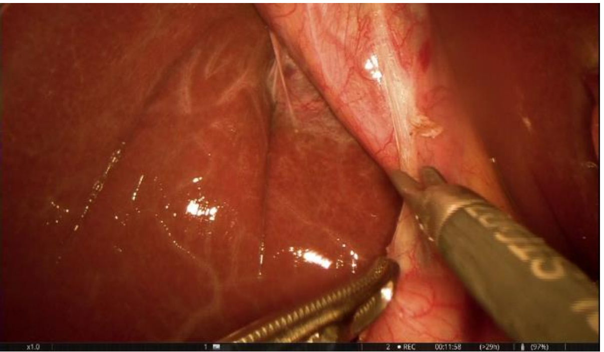

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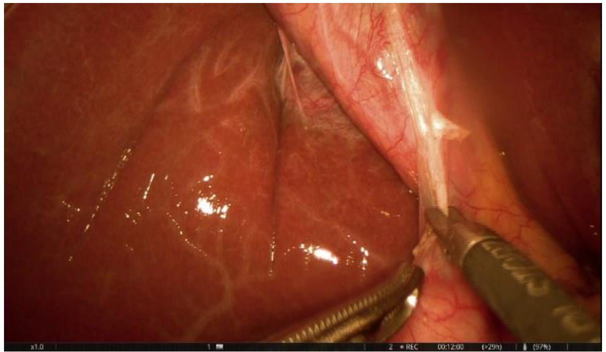
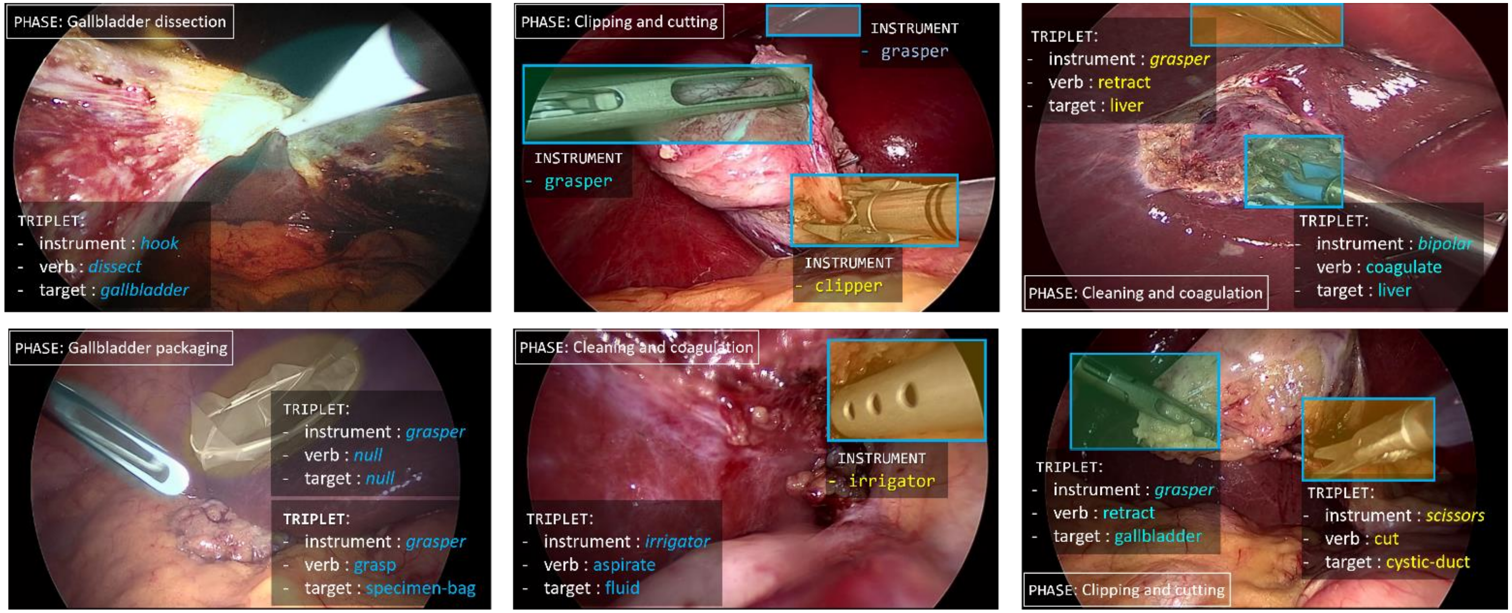


Action name
Grasp
Hold
Cut
Clip

Workflow Analysis Tasks: Activity/Triplet Detection

- A combination of instrument, target (e.g. organ) and action
  - <instrument, action, target>



Twinanda, Andru P., et al., IEEE TMI 2016: Endonet: a deep architecture for recognition tasks on laparoscopic videos
Nwoye, C. I., et al., MIA 2022: Rendezvous: Attention Mechanisms for the Recognition of Surgical Action Triplets in Endoscopic Videos

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Workflow Analysis Tasks: Skill assessment

- Determine how well a surgeon is performing
  - Useful for training
  - Detect if surgeon is tired
  - Often subjective
  - Different criteria

Ranking component	Depth perception	Bimanual dexterity	Efficiency	Tissue handling	Case difficulty
Range	1-5	1-5	1-5	1-5	1-5

Workflow analysis

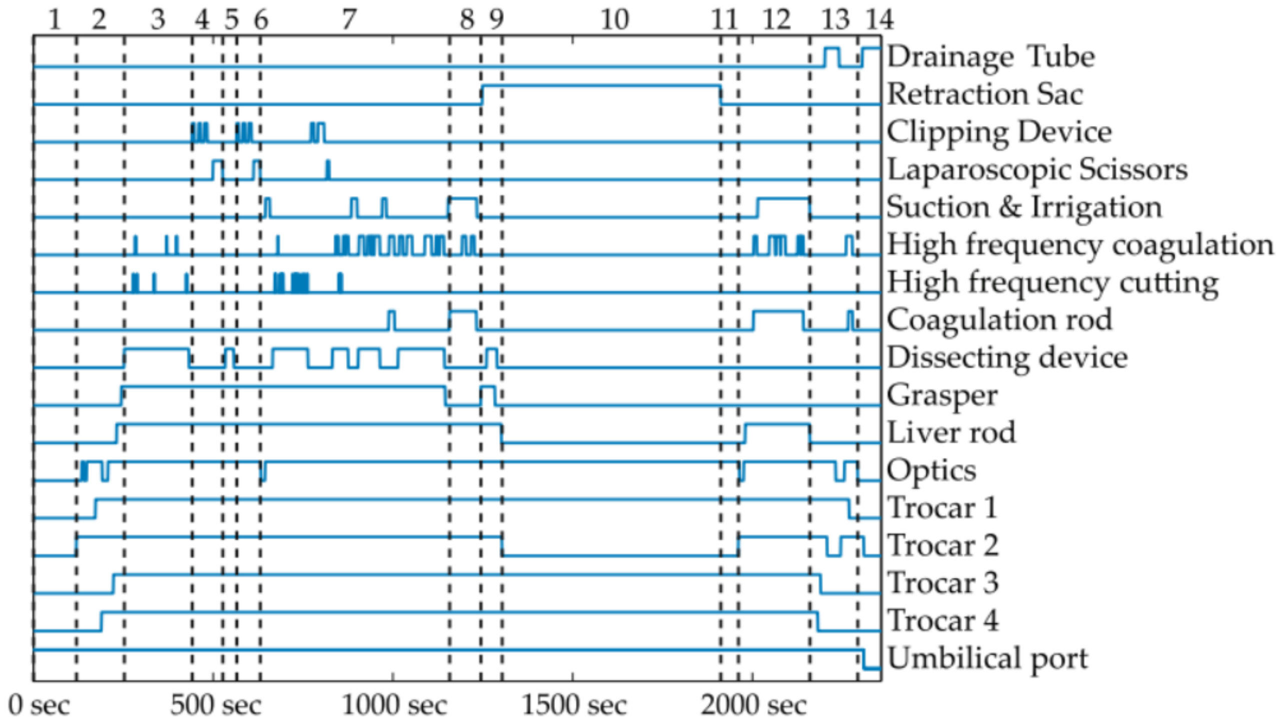
- Workflow and skill analysis difficult some single frames
  - Movement between frames often valid
  - Changes in tissue

- Often frames have to be viewed in temporal context
  - Propagate methods over time

- Some machine learning algorithms suited for temporal modelling, e.g.
  - **Hidden Markov Models**
  - 3D CNNs
  - **Recurrent Neural Networks**

Methods workflow analysis

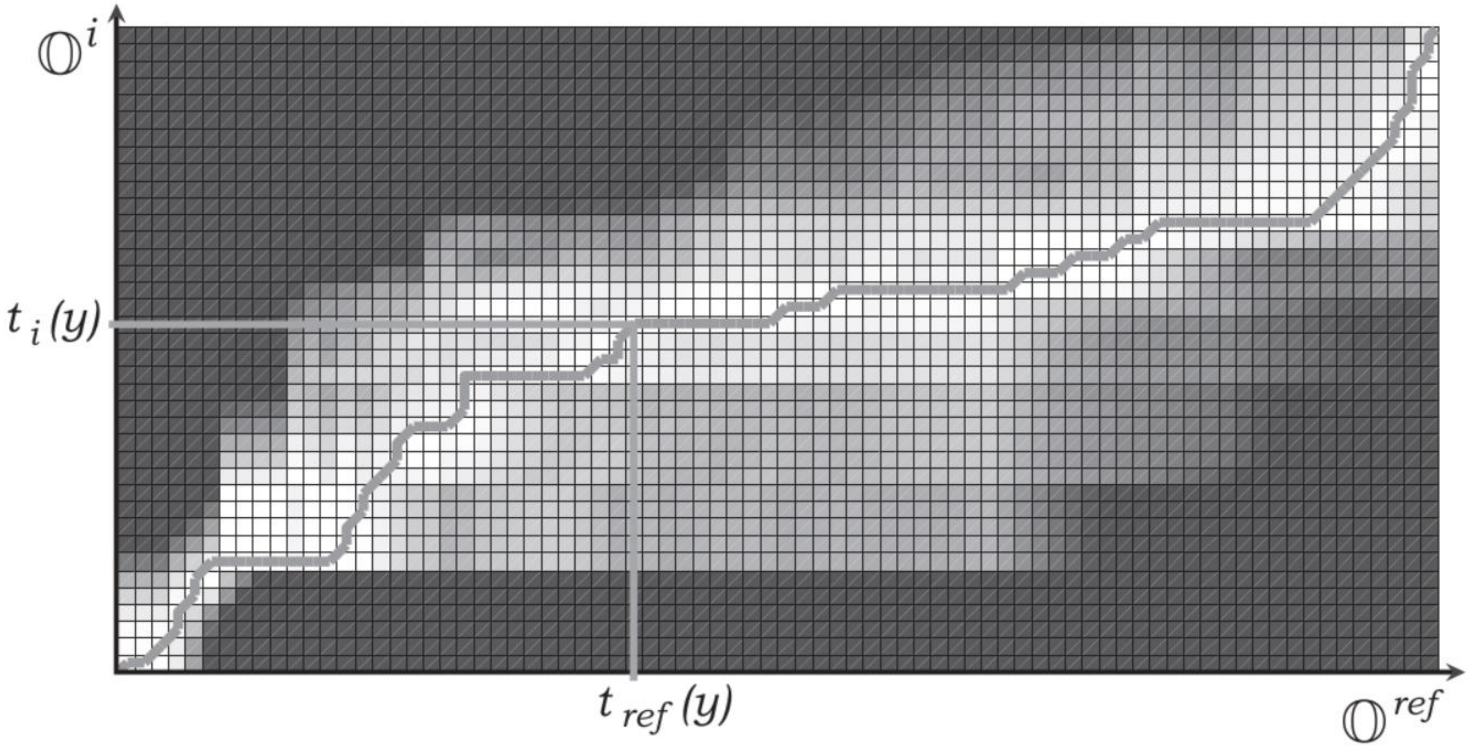
- First approaches relied on manually annotated signals, e.g. based on tool usage



Blum, Tobias, et al., IJCARS 2008: Workflow mining for visualization and analysis of surgeries.
Padoy, Nicolas, et al., MIA 2012: Statistical modeling and recognition of surgical workflow.

Methods workflow analysis

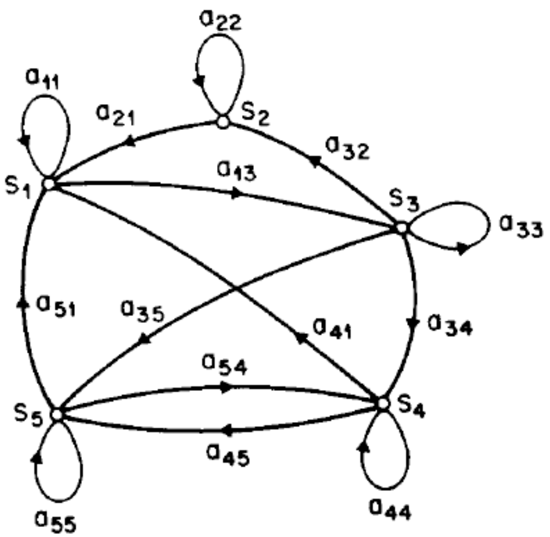
- Dynamic Time Warping (DTW) for temporal alignment of different surgeries



Blum, Tobias, et al., IJCARS 2008: Workflow mining for visualization and analysis of surgeries.
Padoy, Nicolas, et al., MIA 2012: Statistical modeling and recognition of surgical workflow.

Hidden Markov Models

- Have been successfully used for speech-, text- and gesture recognition
- Based on Markov-Chains:



N discrete states:

$$S = \{S_1, S_2, \ldots, S_N\}$$

Time point of state transitions:

$$t = 1, 2, \ldots$$

Current state at time point t:

$$q_t$$

- Transition between states occurs with a certain probability
- Probability is only dependent on the current state

Markov Chain example: Weather

Every day at noon, the weather is examined:

State 1: Rain (Or snow)

State 2: Cloudy

State 3: Sunny

Matrix of transition properties:

$$A = \left\{a_{ij}\right\} = \begin{bmatrix} 0.4 & 0.3 & 0.3 \\ 0.2 & 0.6 & 0.2 \\ 0.1 & 0.1 & 0.8 \end{bmatrix}$$

Question: If it is sunny today, what is the probability that the weather of the next 7 days will be

{  }?

Example: Weather

Observation: $O = S_3, S_3, S_3, S_1, S_1, S_3, S_2, S_3$

Solution:

$$\begin{aligned}
P(O|\text{Modell}) =& P(S_3, S_3, S_3, S_1, S_1, S_3, S_2, S_3|\text{Modell}) \\
=& P(S_3) \cdot P(S_3|S_3) \cdot P(S_3|S_3) \cdot P(S_1|S_3) \\
& \cdot P(S_1|S_1) \cdot P(S_3|S_1) \cdot P(S_2|S_3) \cdot P(S_3|S_2) \\
=& \pi_3 \cdot a_{33} \cdot a_{33} \cdot a_{31} \cdot a_{11} \cdot a_{13} \cdot a_{32} \cdot a_{23} \\
=& 1 \cdot 0.8 \cdot 0.8 \cdot 0.1 \cdot 0.4 \cdot 0.3 \cdot 0.1 \cdot 0.2 \\
=& 1.536 \times 10^{-4}
\end{aligned}$$

with

$$\pi_i = P(q_1 = S_i), \quad 1 \leq i \leq N$$

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Hidden Markov Models

Until now:

- Events (states) are directly observable

Now:

- Observing is a stochastic function of the state

  → States can only be observed indirectly

HMMs consist of two stochastic processes:

The first stochastic process can only be observed indirectly through a different set of stochastic processes that produce a observation sequence.

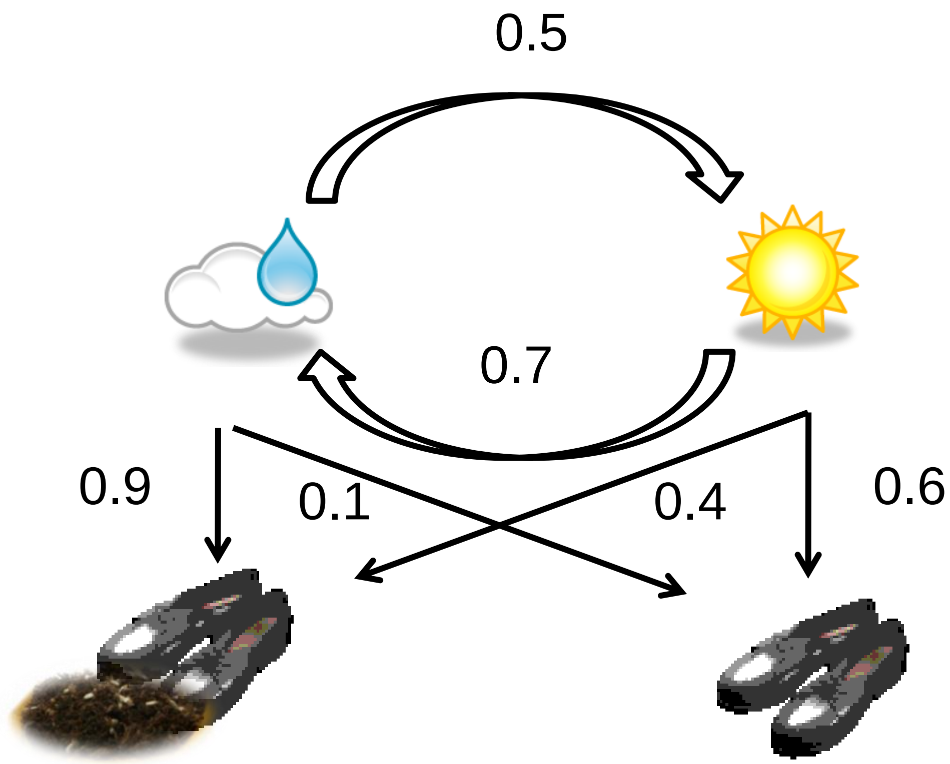
Example: Prisoner

A prisoner wants to know the weather outside:

State 1: Rain (or snow)

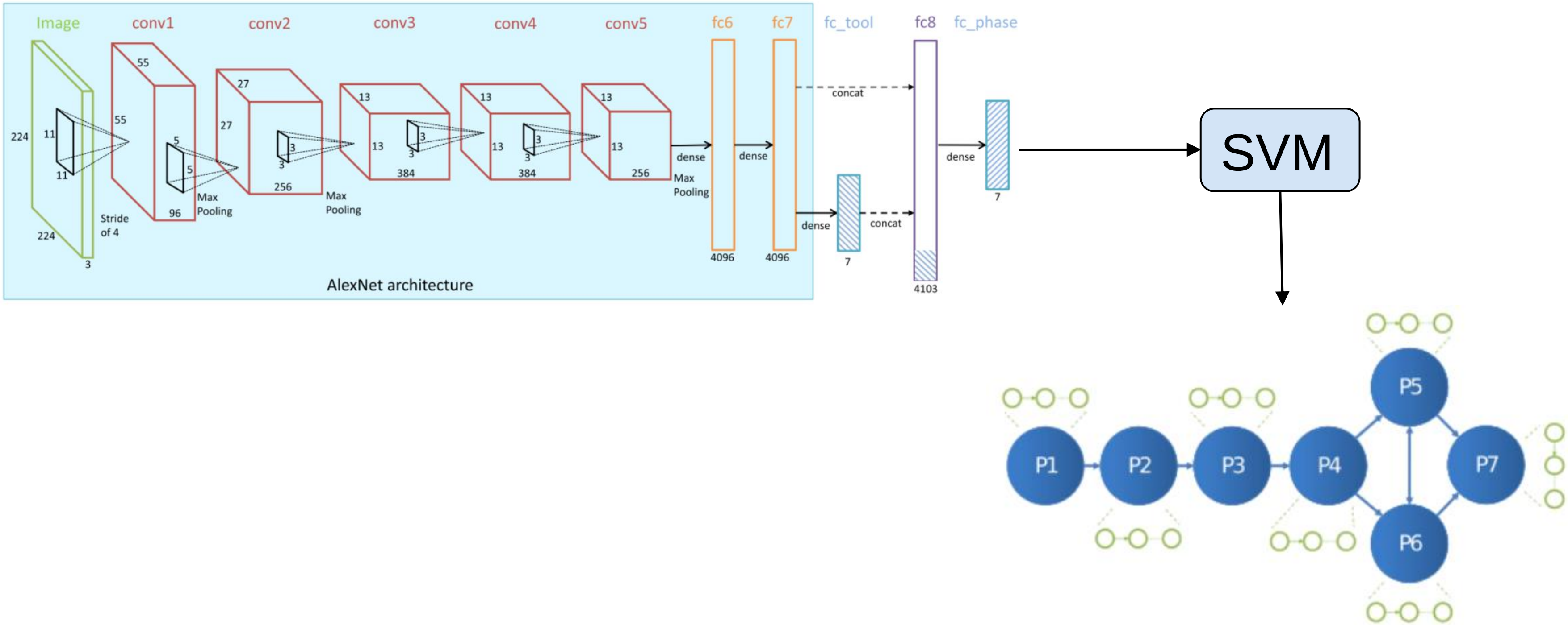
State 2: sunny

Model:



Methods workflow analysis

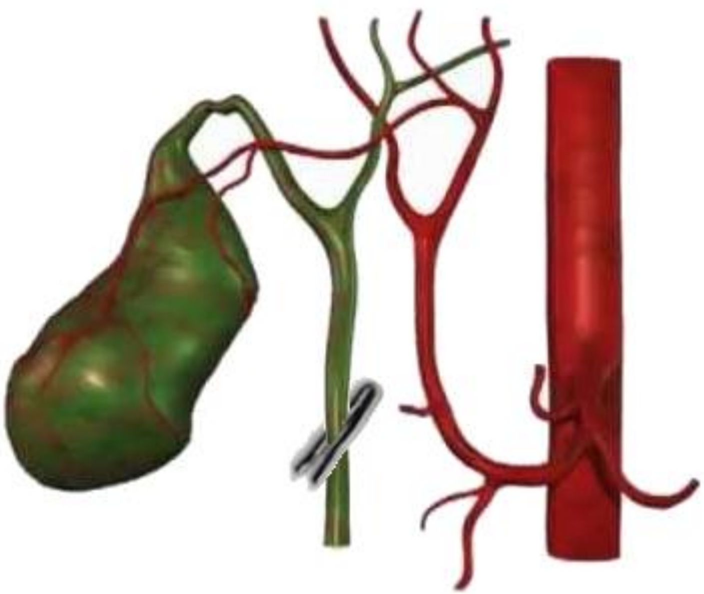
- EndoNet: First deep learning-based approach



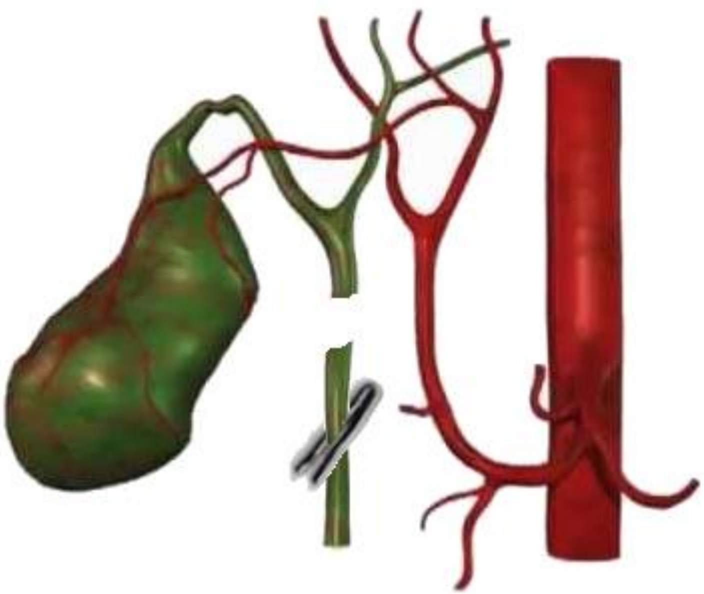
Twinanda et al., IEEE TMI 2017: EndoNet: A Deep Architecture for Recognition Tasks on Laparoscopic Videos

Recurrent neural networks (RNNs)

- Illustrated example
  - Excerpt gallbladder removal, two steps we want to recognize:

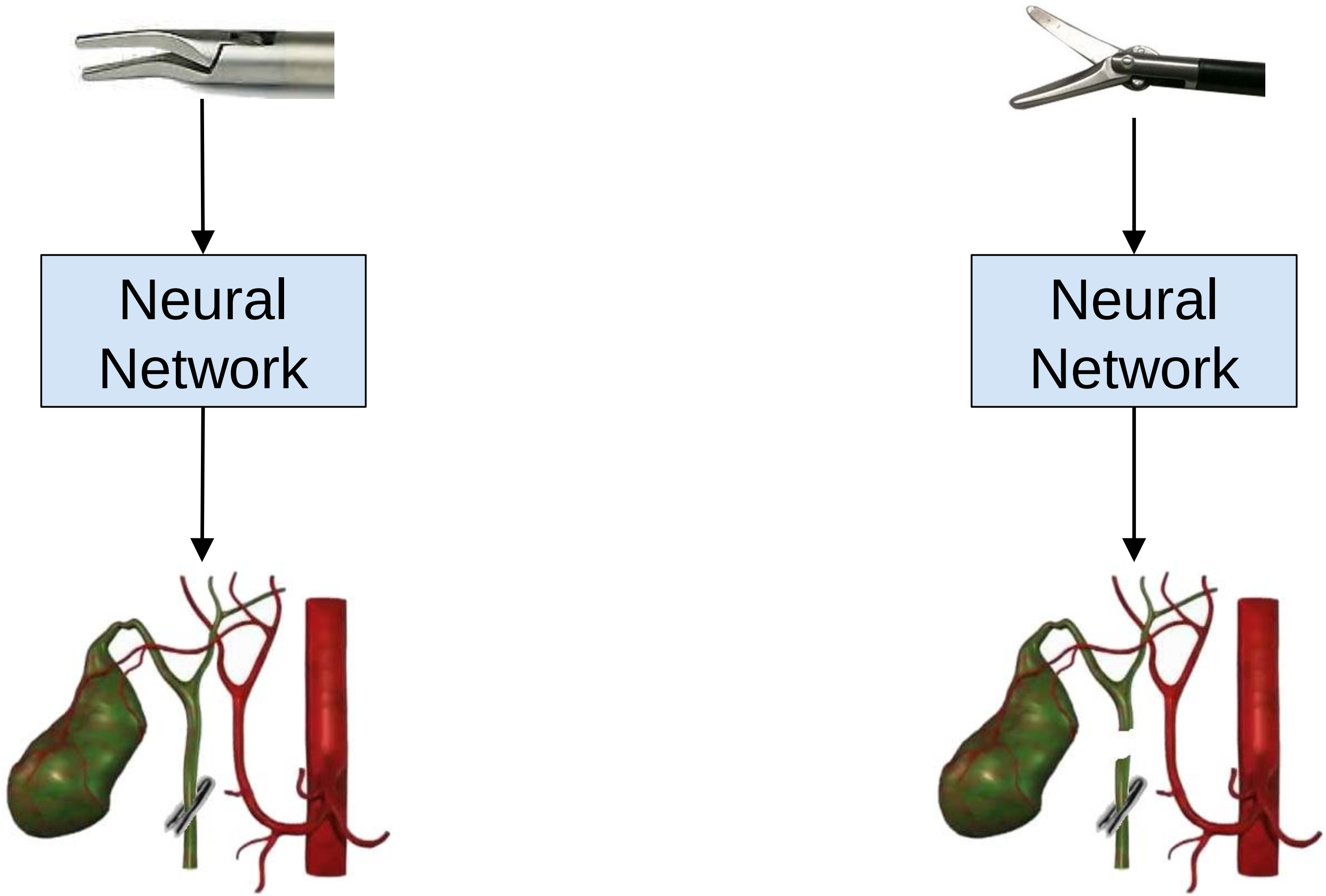


Clipping cystic duct



Cutting cystic duct

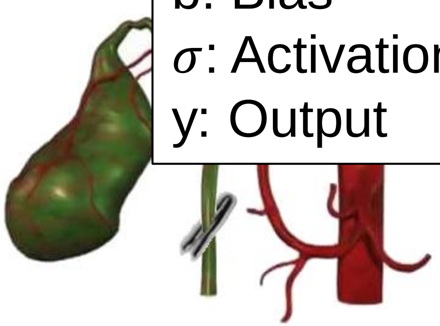
Standard Feed-forward neural network

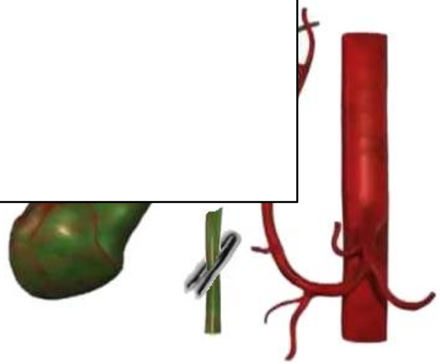


Standard Feed-forward neural network

$$y = \sigma(w \cdot x + b)$$

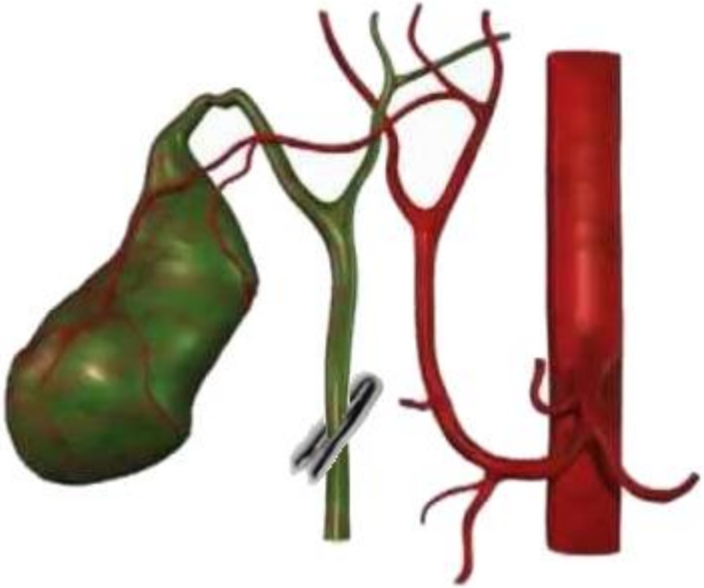
x: Input
w: Weight
b: Bias
σ: Activation function
y: Output



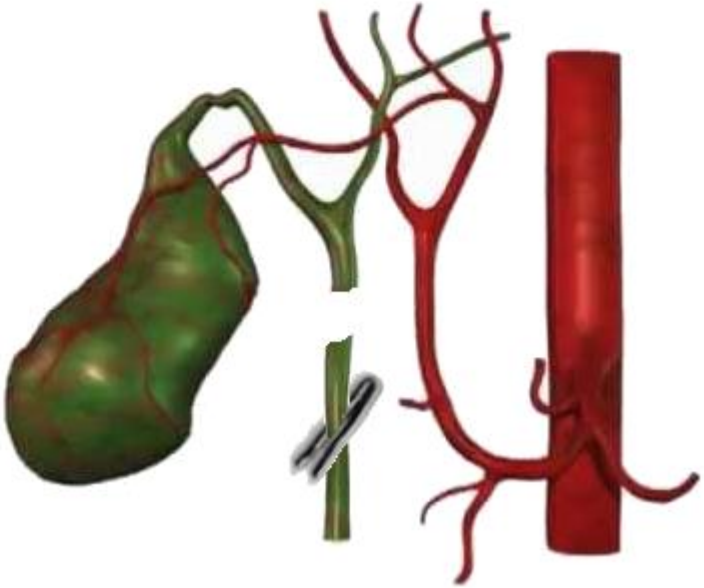


Recurrent neural networks (RNNs)

- Illustrated example
  - Excerpt gallbladder removal, four steps we want to recognize:



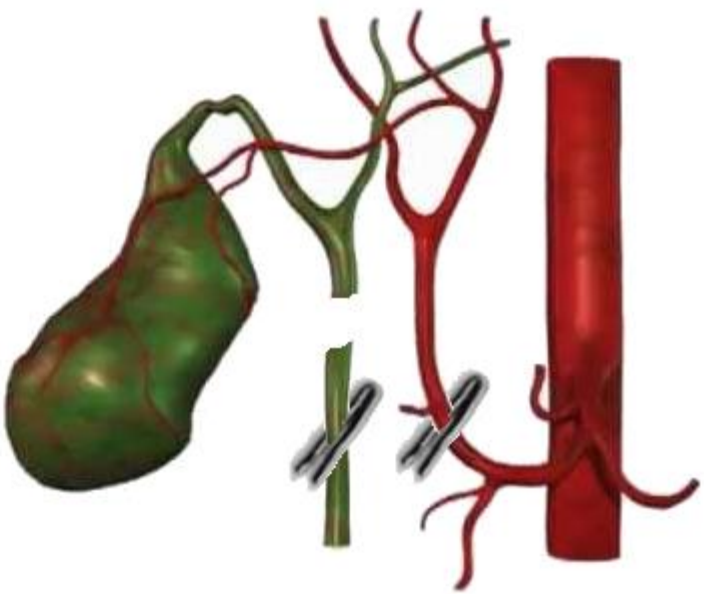
Clipping cystic duct



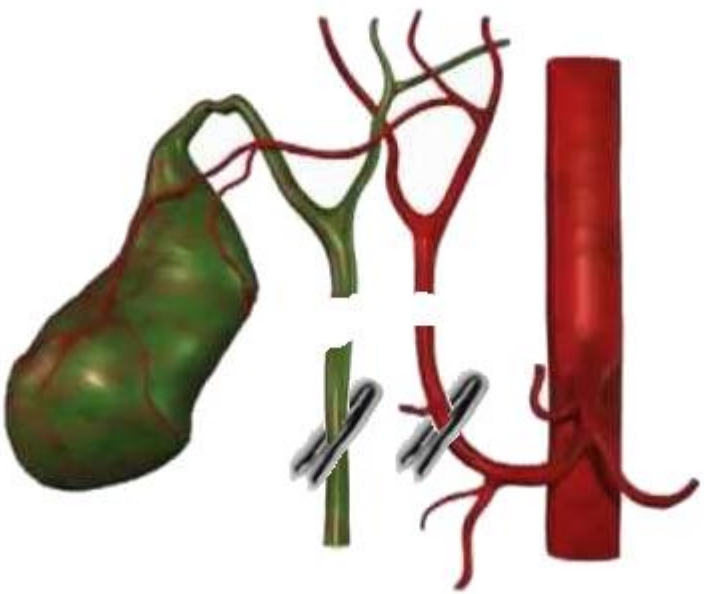
Cutting cystic duct

Recurrent neural networks (RNNs)

- Illustrated example
  - Excerpt gallbladder removal, **four** steps we want to recognize:

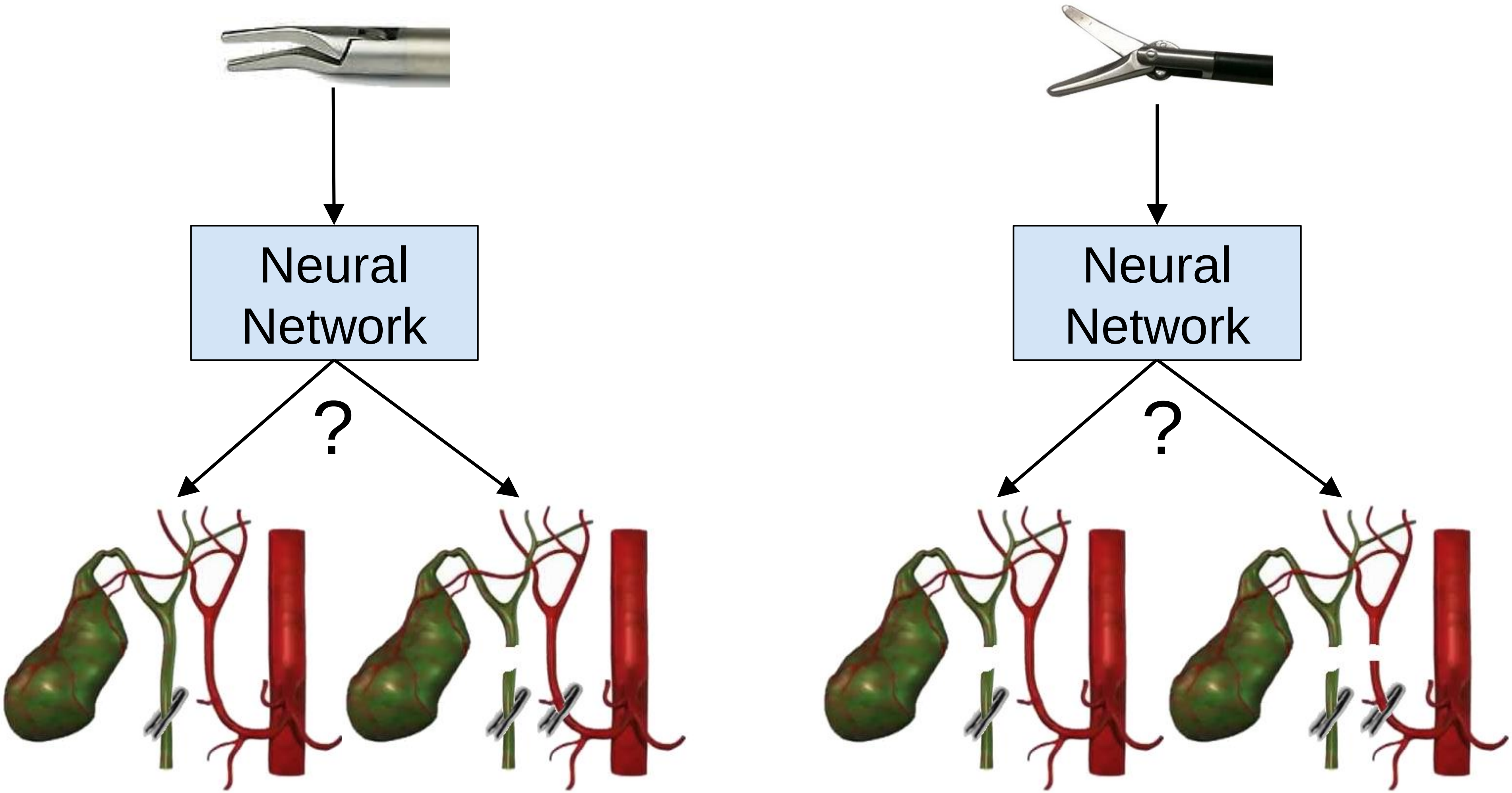


Clipping cystic artery

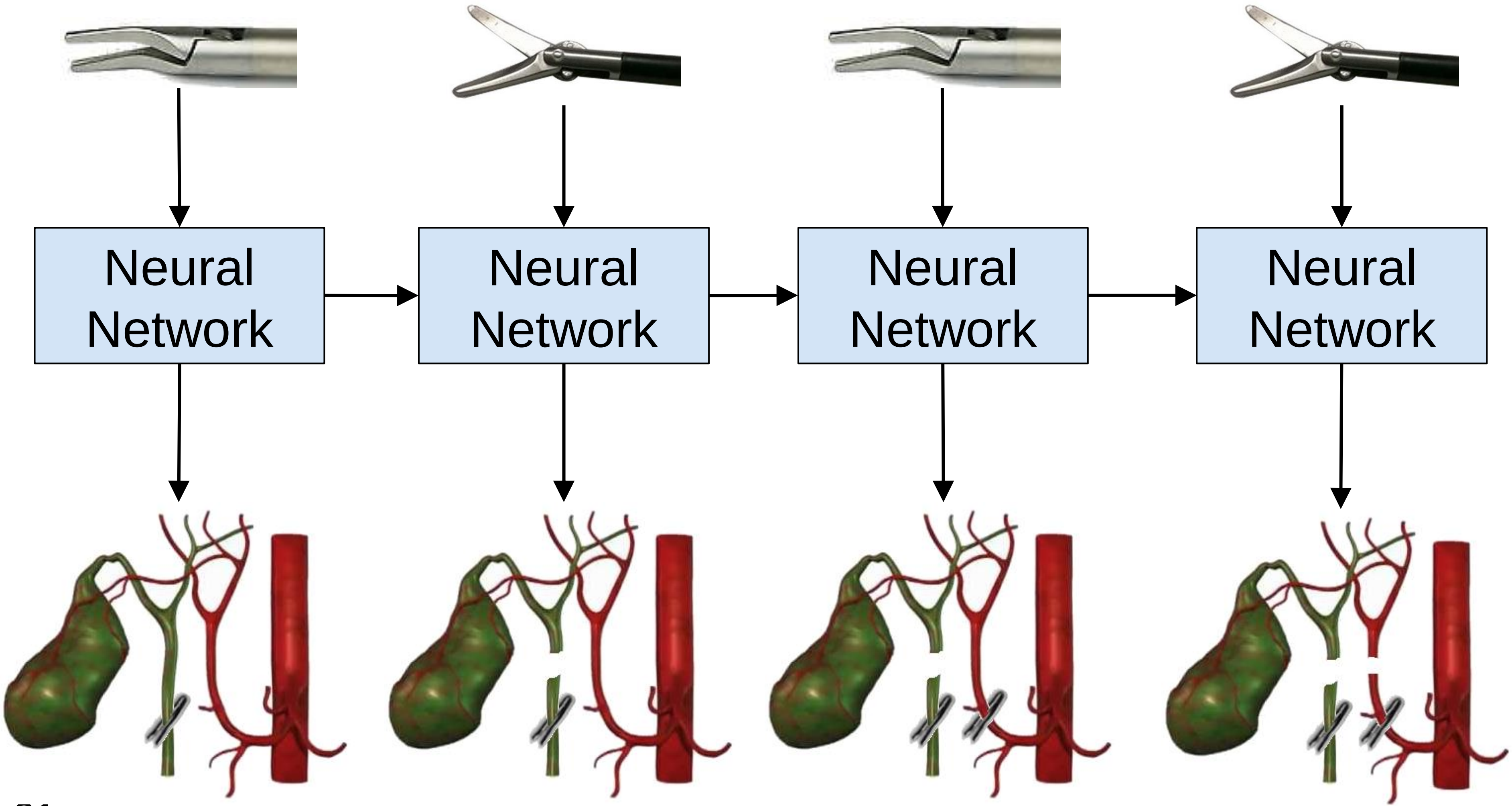


Cutting cystic artery

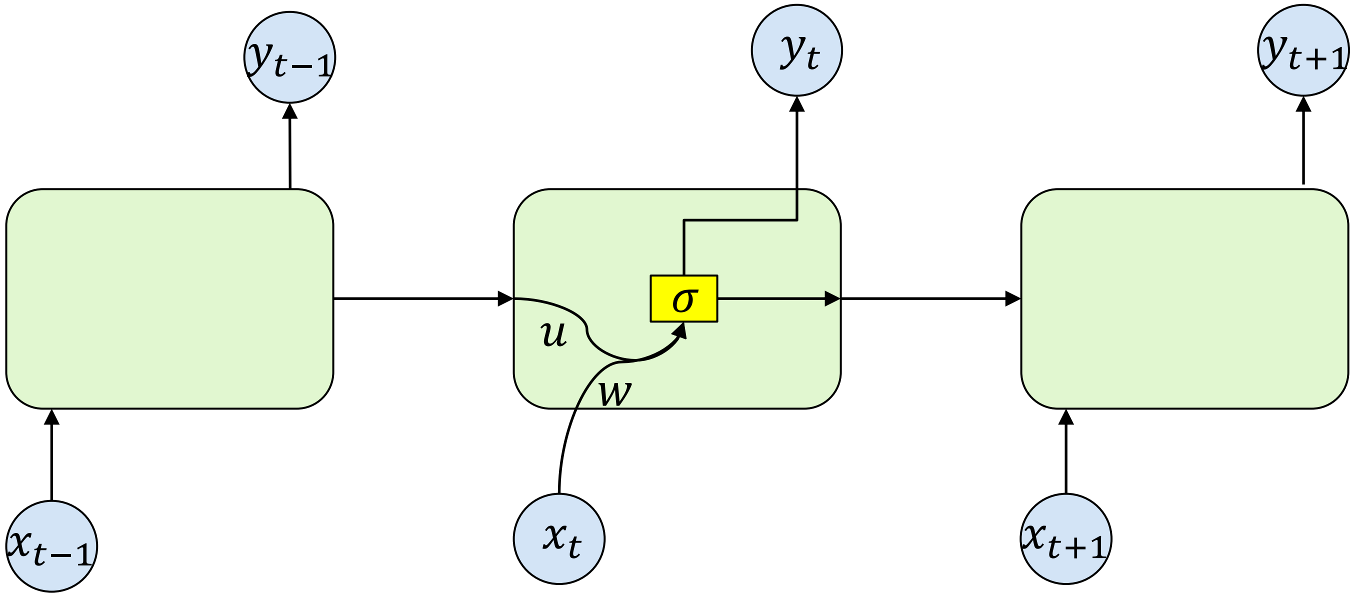
Standard Feed-forward neural network



Recurrent neural network (RNNs)



Recurrent neural network (RNNs)

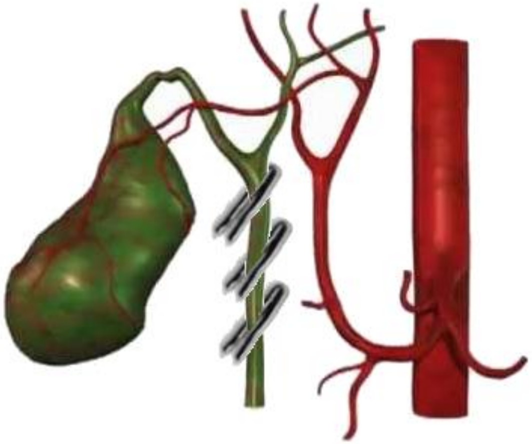


$$y_t = \sigma(w \cdot x_t + u \cdot y_{t-1} + b)$$

x_t: Input
w: Layer weight
u: Recurrent weight
b: Bias
σ: Activation function
y_t: Output
y_{t-1}: Output previous step

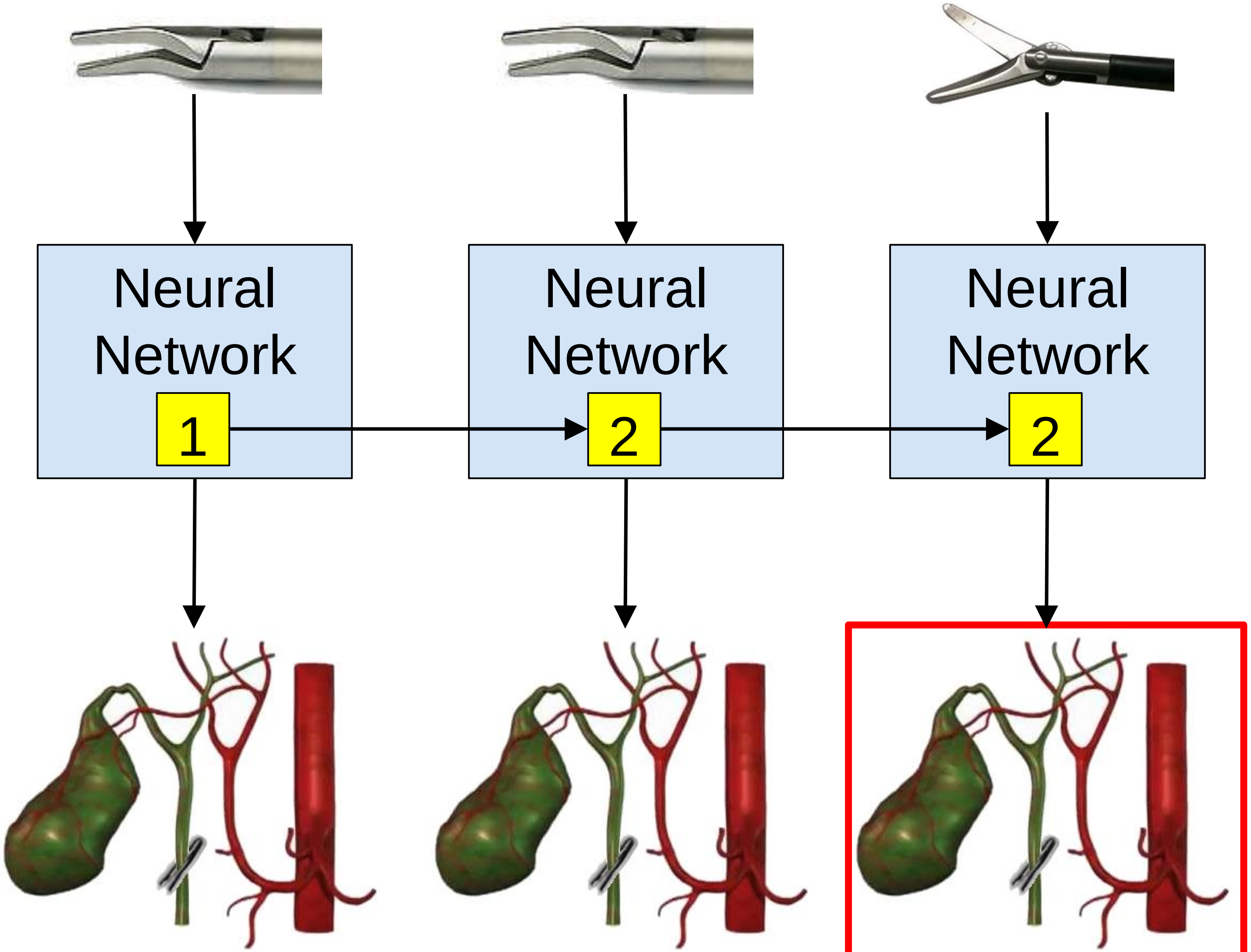
Advanced recurrent neural network

- Problem with vanishing gradient
  - Information from the beginning of the sequence has little impact on the output at the end of the sequence
  - => Basic RNNs pose something more akin to a “short-term memory”

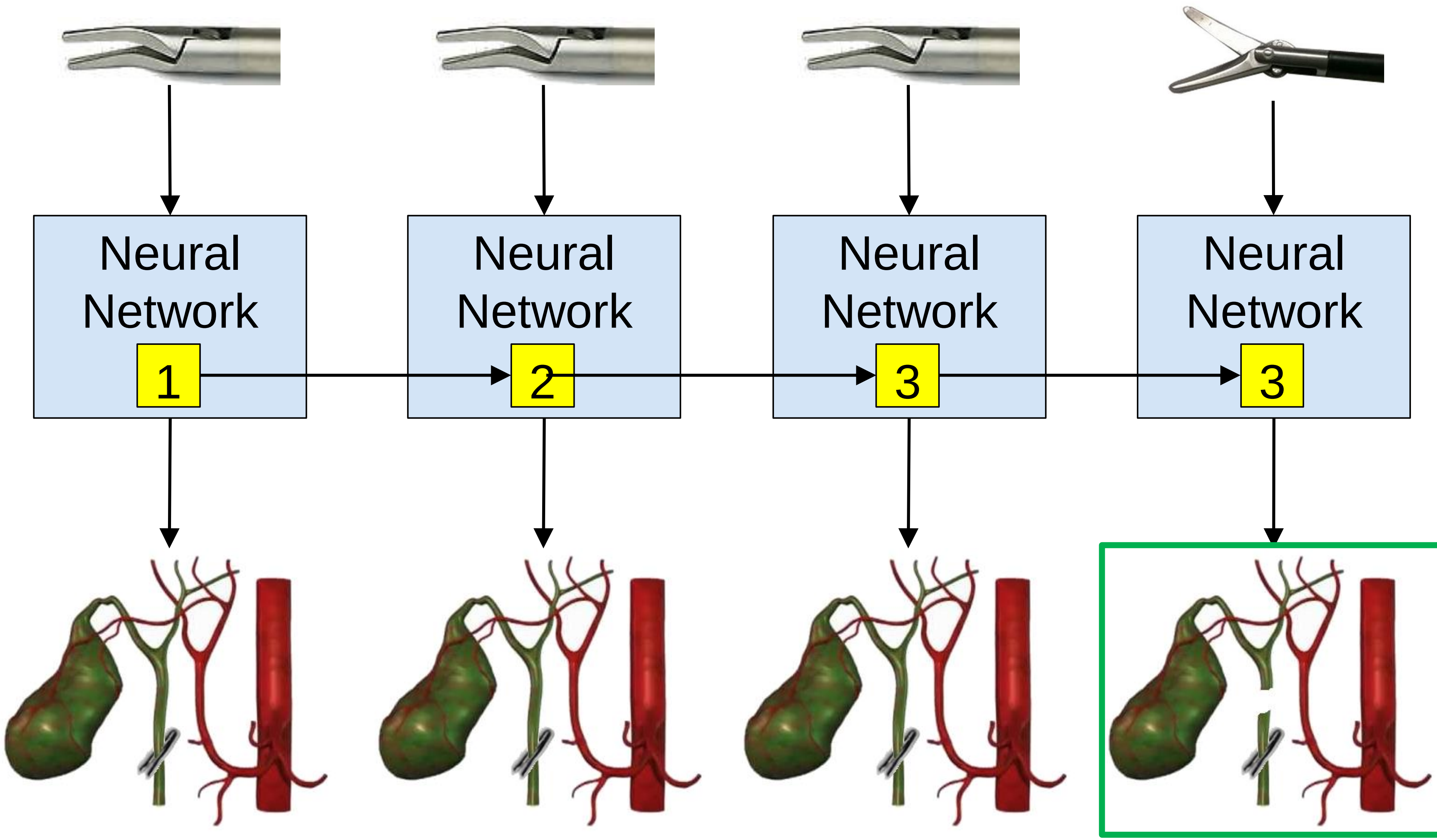


- Illustrative example
  - Clipping actually requires three clips
  - Design a system that warns surgeons if not enough clips were set before cutting
  - => System actually has to count clips, basic RNNs might “forgot” progress
  - Solution 1: Introduce more steps/states, one for each clip
  - Solution 2: Introduce a more “long-term” memory

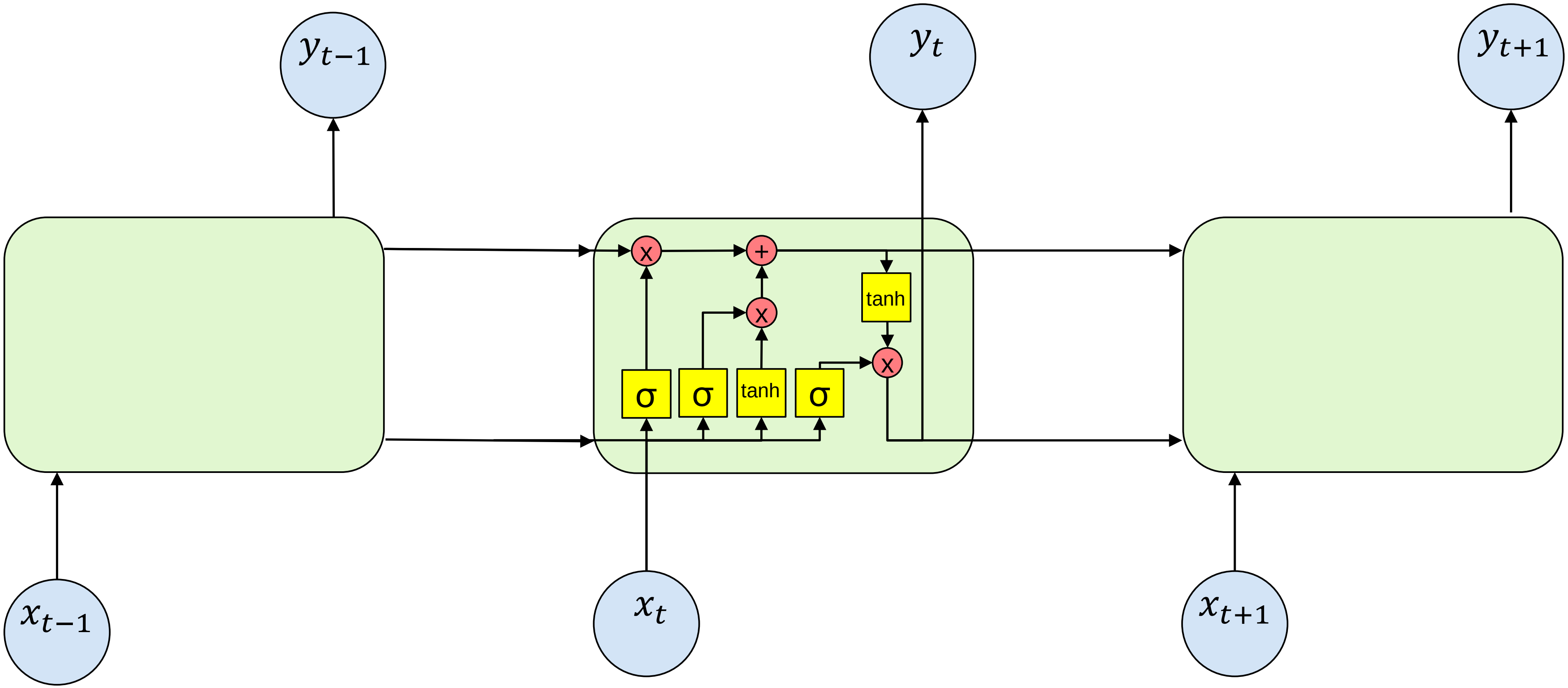
Recurrent neural network (RNNs)



Recurrent neural network (RNNs)



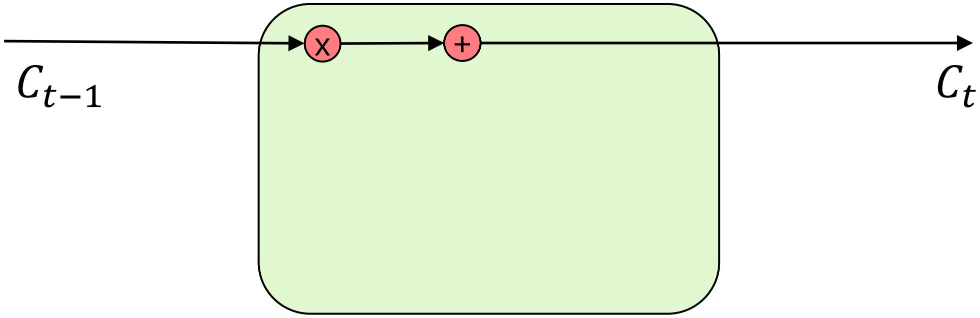
Long-short term memory (LSTM) unit



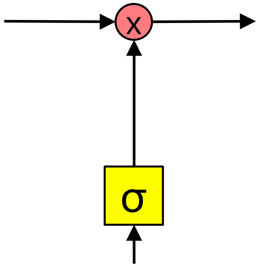
- Designed to avoid long-term dependency problem
- Can learn to remember/forget information

LSTM - Components

- Cell state: the “memory” of the LSTM

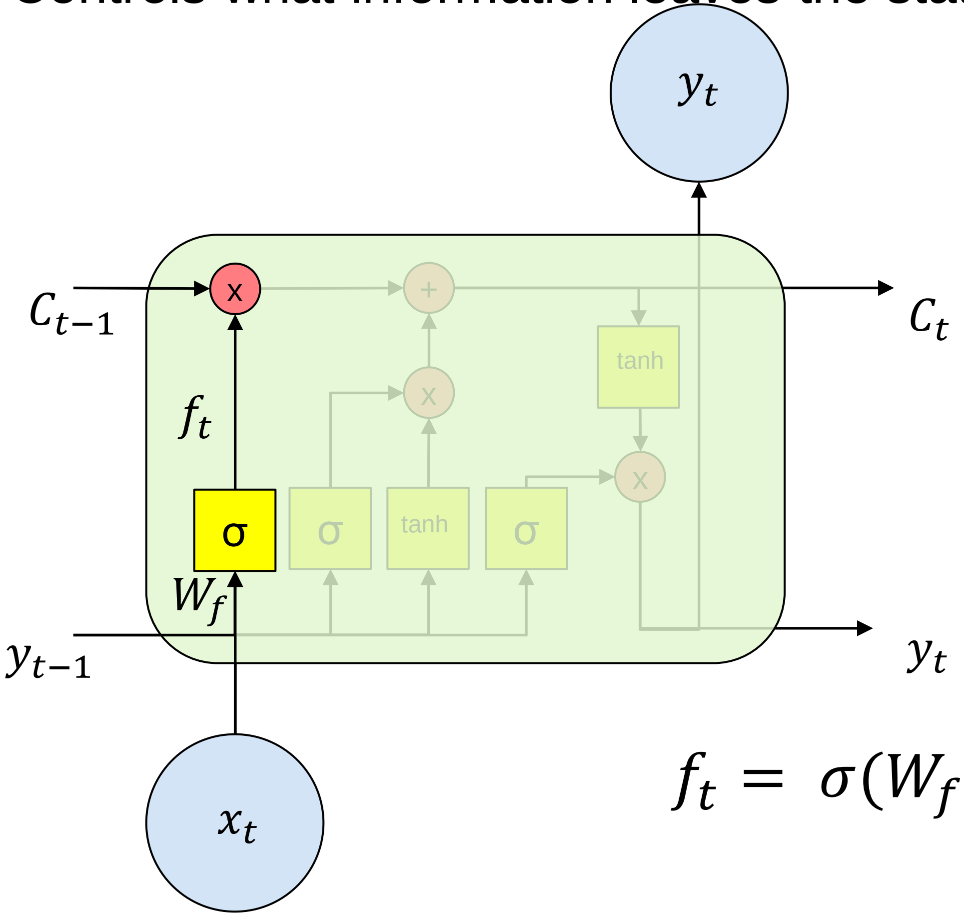


- Gates: control which information is added or removed from the cell state



LSTM - Components

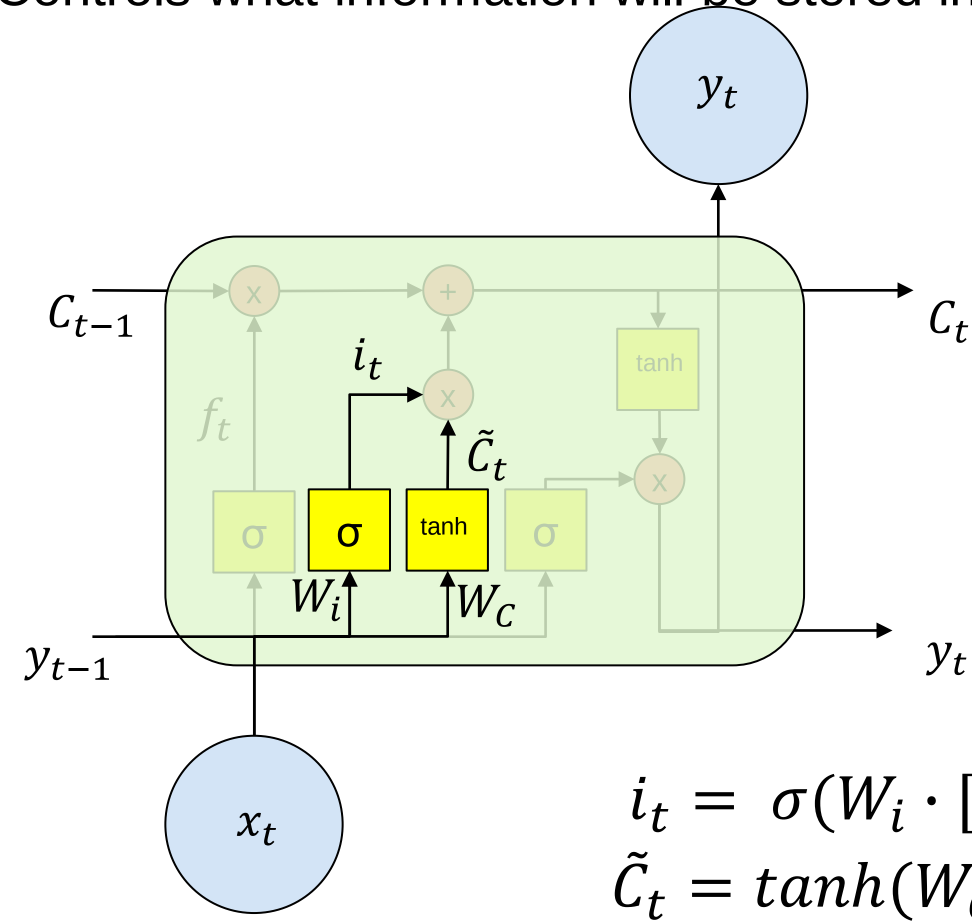
- Forget gate: Controls what information leaves the state



$$f_t = \sigma(W_f \cdot [y_{t-1}, x_t] + b_f)$$

LSTM - Components

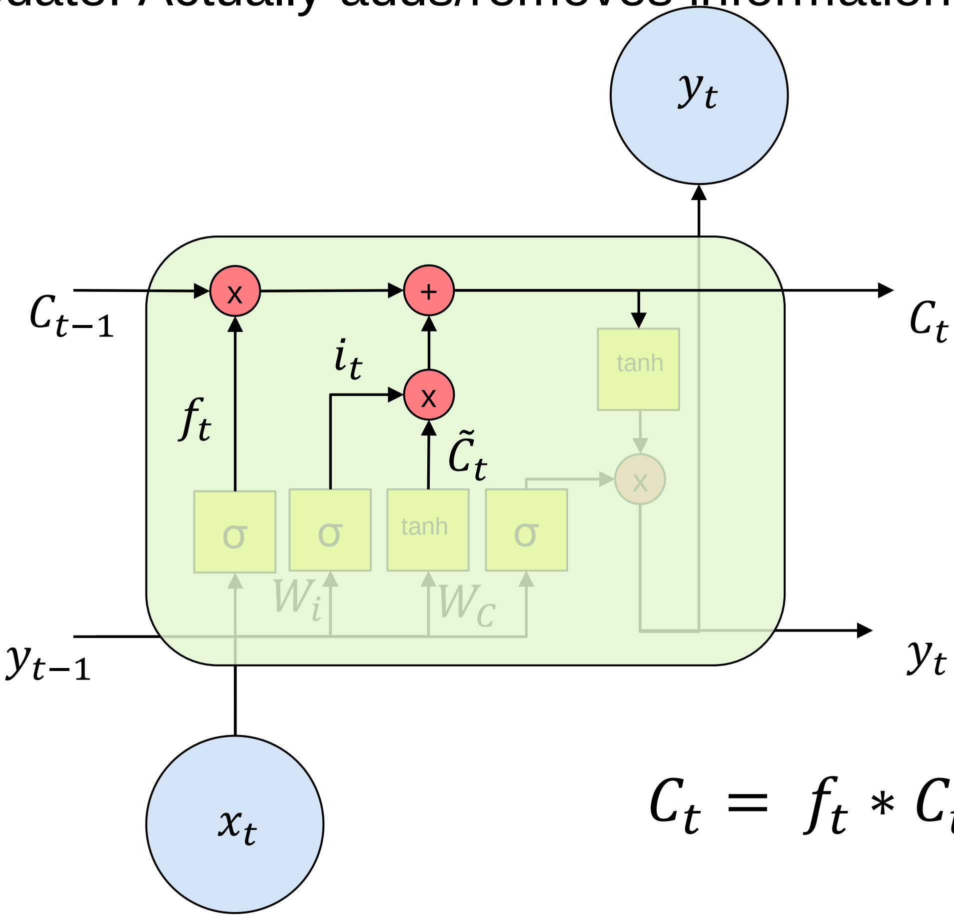
- Input gate: Controls what information will be stored in the cell



$$i_t = \sigma(W_i \cdot [y_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = tanh(W_C \cdot [y_{t-1}, x_t] + b_C)$$

LSTM - Components

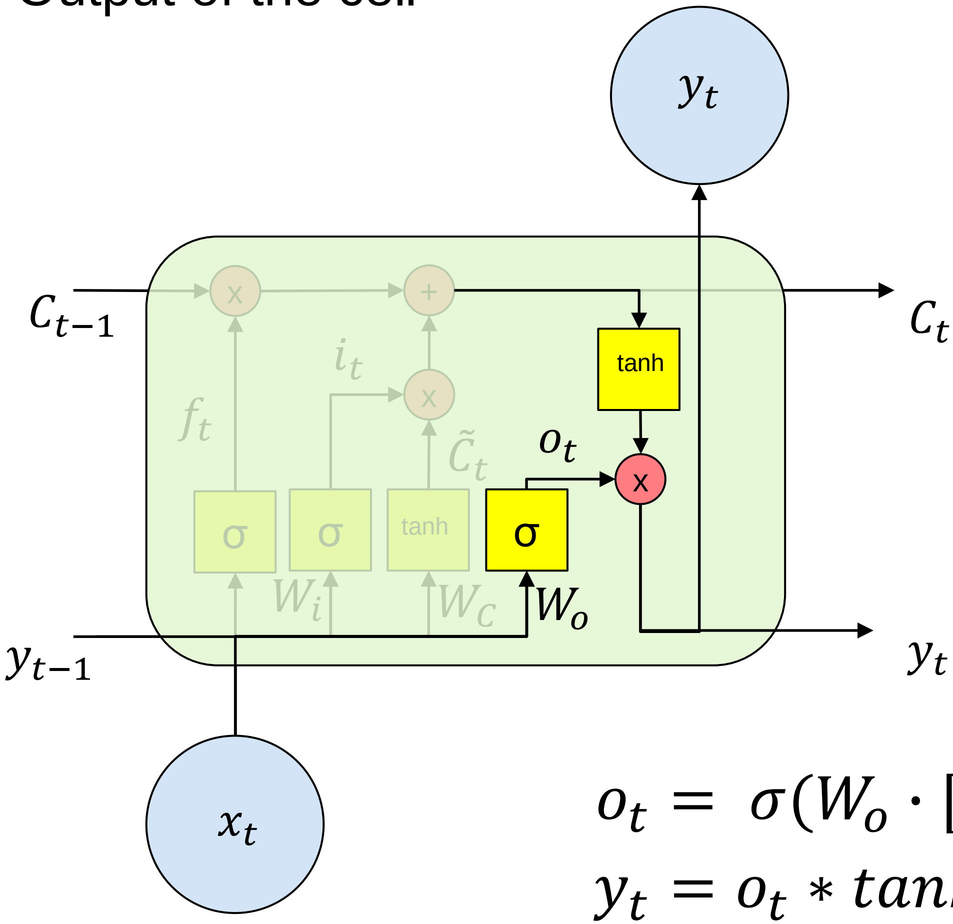
- Cell state update: Actually adds/removes information from the cell state



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t)$$

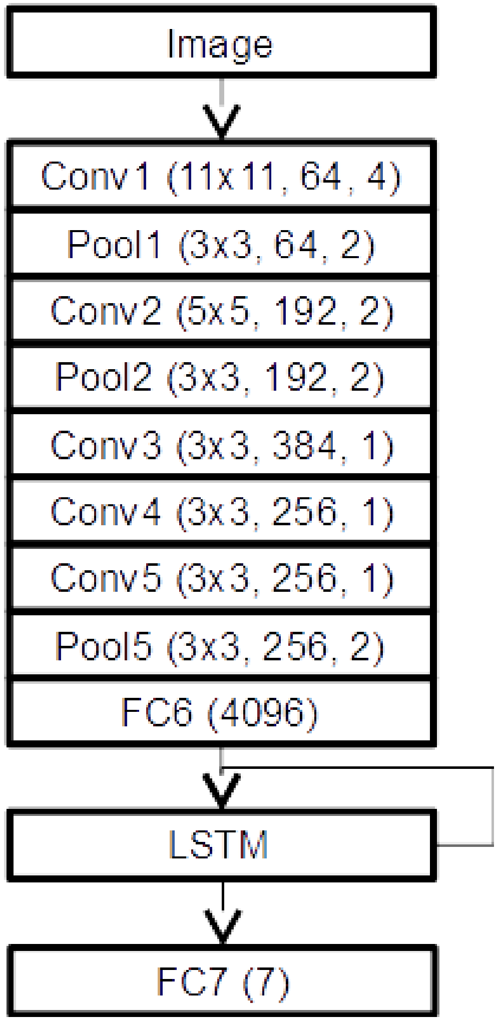
LSTM - Components

- Output gate: Output of the cell



$$o_t = \sigma(W_o \cdot [y_{t-1}, x_t] + b_o)$$
$$y_t = o_t * tanh(C_t)$$

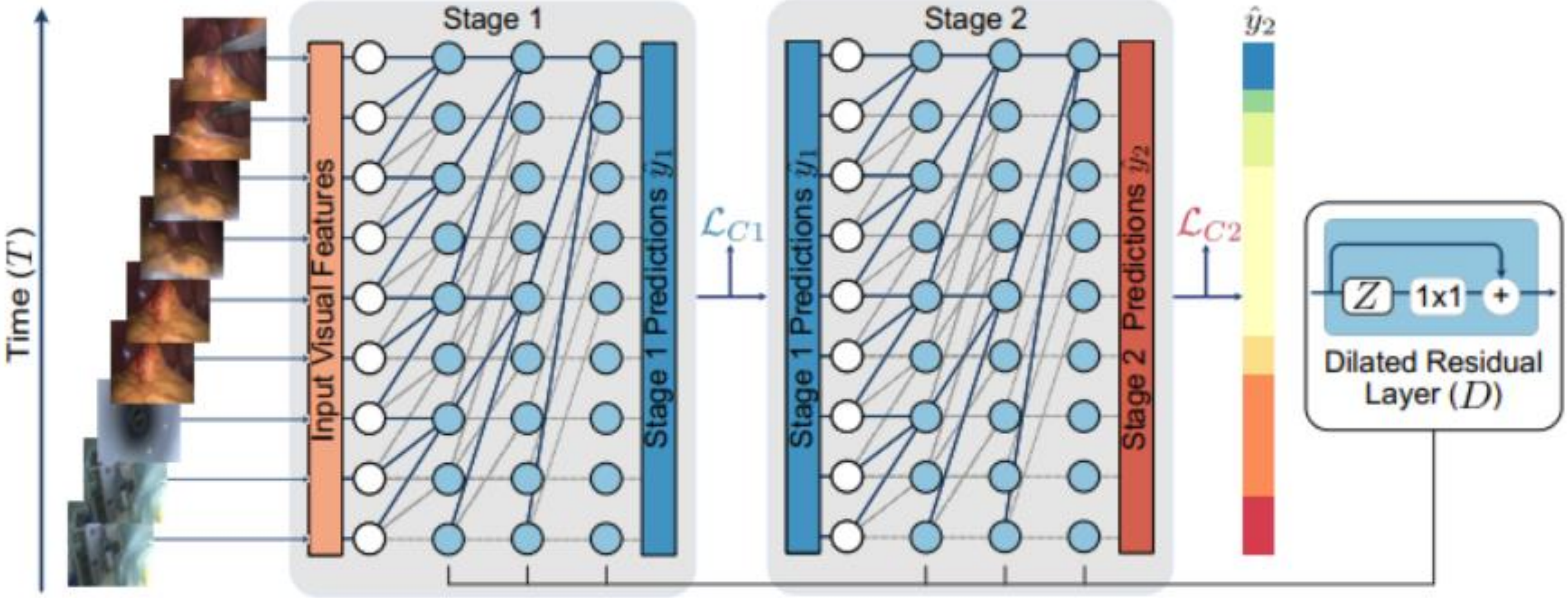
LSTM - Workflow



Funke, Isabel, et al. "Temporal coherence-based self-supervised learning for laparoscopic workflow analysis." *OR 2.0 Context-Aware Operating", Proceedings 5*. Springer International Publishing, 2018.

Methods workflow analysis

- Alternative to LSTM: TeCNO
  - Dilated causal convolutions



Czempiel et al., MICCAI 2020: EndoNet: A Deep Architecture for Recognition Tasks on Laparoscopic Videos

Surgical Training Simulation

Simulator

[Simbionix Ltd.]

Motivation – Systems for Surgical Simulation

What has to be simulated?

- Appearance of organs
- Physiological functions (e.g. bloodflow)
- Smoke
- Instrument behavior
- Deformation of soft-tissue
  (Cutting, pulling, suturing, etc.)

Visualization

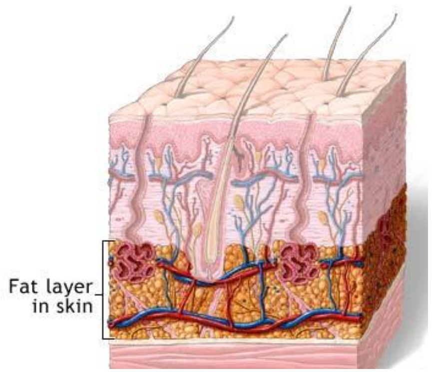
⇕ „Physics Engine“

Simulation

Simulation in real-time

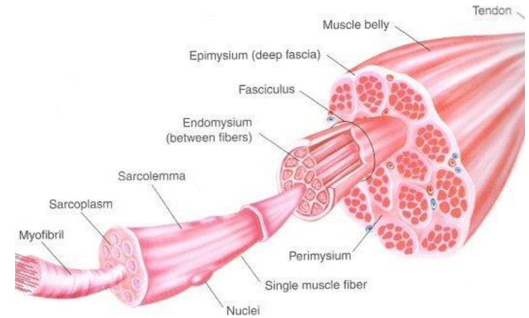
- 30 Hz for visual feedback
- 1000 Hz for haptic feedback

What is soft-tissue?



Skin

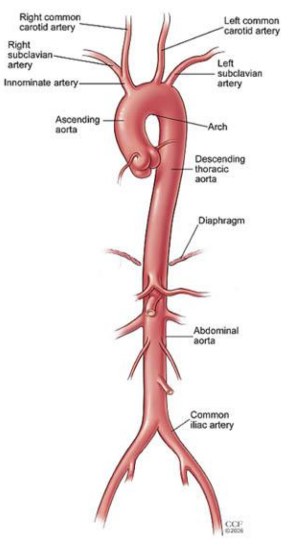
Fat



Muscles

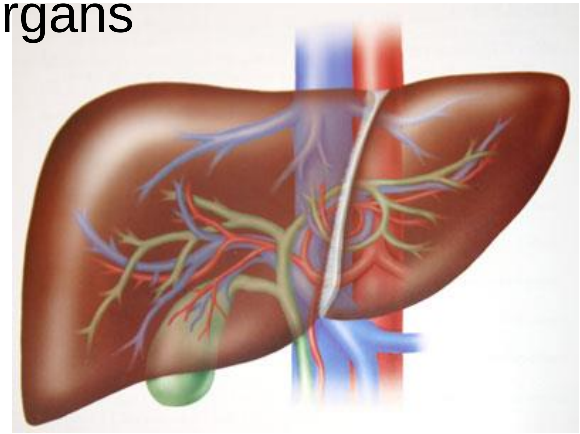
Soft-tissue

Vessels



Connective tissue

Organs



Mechanical properties of soft-tissue

Mechanical properties of biological materials are difficult to determine

- Micro-structure vs. Macro-structure
- Analysis *in vivo* vs. *in vitro*

Here we will present the most important properties and terms

Mechanical properties - Terms

Definitions from computer graphics

Rigid body:

A rigid body is a system of materials in which under all conditions the distance between any two arbitrary points of the body remains constant.

Deformable body:

A deformable body is a system of materials in which the distance between two points can vary over time.

Deformable bodies I

Elastic deformation:

The body goes into a deformed state through the influence of external forces and stores thereby energy. Once the external forces are removed, this energy is given of as kinetic energy.

(Linear-) elastic deformation

The magnitude of the deformation is linear in relation to the external force (e.g. a spring). Deformation is proportional to the force.

Hyper-elastic deformation

The relationship between forces and the magnitude of deformation is non-linear.

Deformable bodies II

Plastic deformation:

During deformation, no energy is stored. The deformation remains once force is removed (e.g. modelling clay).

Viscoelastic deformation:

Through internal friction of the material (-> viscosity of fluids) during the return into the original state, deformation energy is converted into heat. Friction is depended on the speed of the deformation.

→ In reality, no pure, elastic materials exist, there are only viscoelastic materials

→ Soft-tissue is a viscoelastic material!

Soft-tissue modelling - Categorization

- Physical modelling
  - Based on fundamental physical principles, the real behavior is modelled
  - Real behavior = realistic physics
  - Example: Finite-Element-Method (FEM)
  - Properties: slow (long computational time), but exact, can be used for predictions

- Phenomenological modelling
  - Adaption to real behavior through optimization of parameters
  - Real behavior = realistic appearance
  - Examples: ChainMail, Nodal Networks
  - Properties: fast, but less accurate, not suitable for predictions

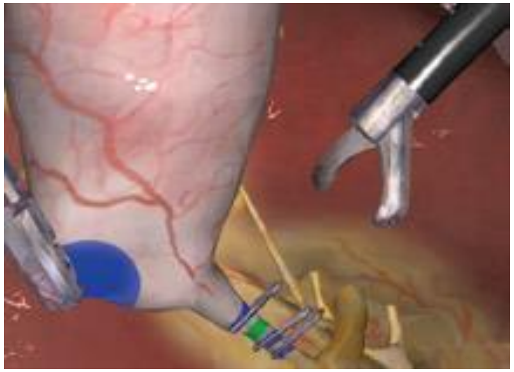
Phenomenological modelling

Meaning

- Only model of behavior
- Not a physically correct model!

Applications

- Surgical simulators
- Soft-tissue registration



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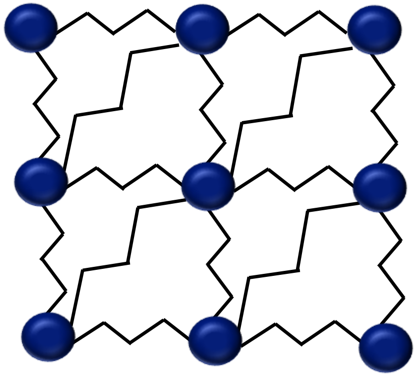
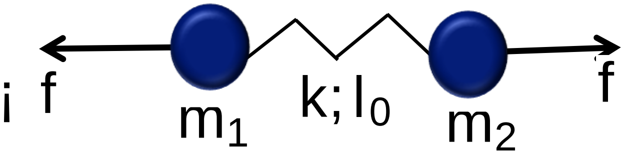


Mathematical modelling

- Nodal Networks: Mass-Spring Systems



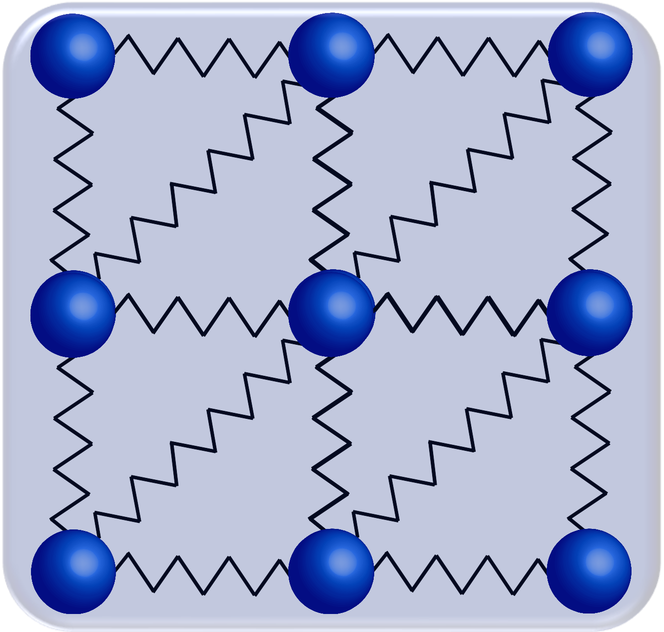
Mass-Spring system

- How can the deformations of a viscoelastic 3D body through external forces be described?

Mass-Spring system

- How can the deformations of a viscoelastic 3D body through external forces be described?
- Idea: Use many simple elements to describe the behavior of a complex system.

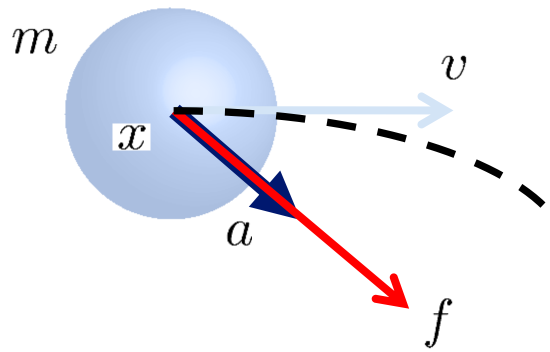
→ Connect rigid points of mass through spring elements.



Dynamics of a point of mass

Configuration of a mass particle:

- Position x [m]
- Velocity v [m/s]
- Mass m [kg]



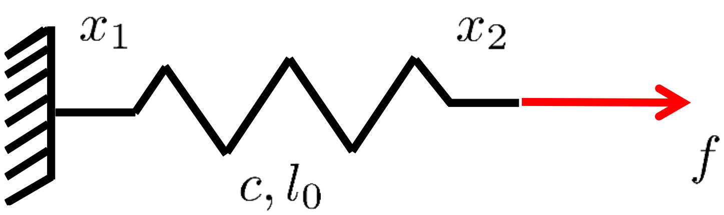
- **Newton's law of motion**

$$F = ma = m\dot{v} = m\ddot{x}$$

Dynamics of a spring

Configuration of a spring (elastic element):

- Length at rest l_0
- Spring constant c (Stiffness)



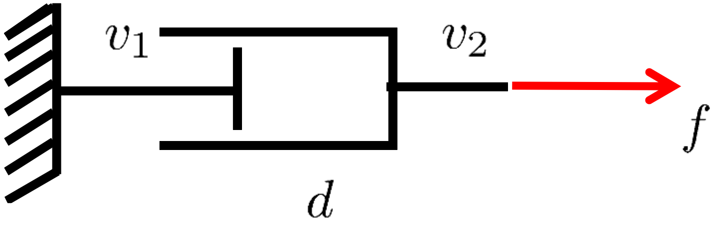
Hooke's law:

$$f = c(x_2 - x_1 - l_0)$$

Dynamics of a damper

Configuration of a damper (viscose element):

- Damping constant d

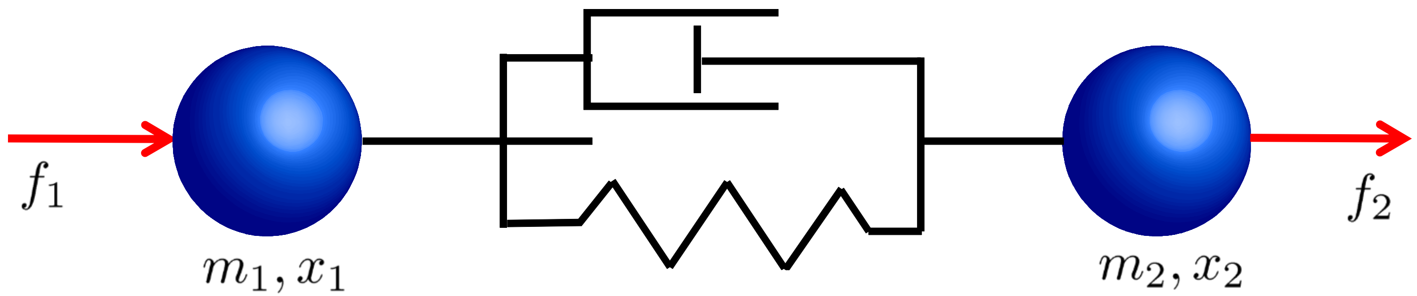


Dynamics:

$$f = d(v_2 - v_1) = d(\dot{x}_2 - \dot{x}_1)$$

Simple Mass-Spring System

- Simple Mass-String-System

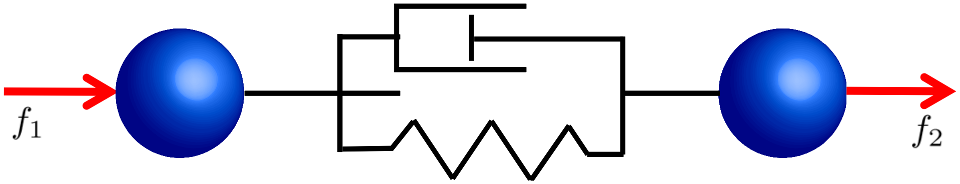


$$f_1 = m_1\ddot{x}_1 + d(\dot{x}_1 - \dot{x}_2) + c(x_1 - x_2 + l_0)$$

$$f_2 = \underbrace{m_2\ddot{x}_2}_{\text{Mass term}} + \underbrace{d(\dot{x}_2 - \dot{x}_1)}_{\text{Dämping term}} + \underbrace{c(x_2 - x_1 - l_0)}_{\text{Stiffness term}}$$

→ System of linear differential equations

Simple Mass-Spring System



- In Matrix form:

$$\begin{pmatrix} f_1 \\ f_2 \end{pmatrix} = \underbrace{\begin{pmatrix} m_1 & 0 \\ 0 & m_2 \end{pmatrix}}_{\text{Mass matrix}} \begin{pmatrix} \ddot{x}_1 \\ \ddot{x}_2 \end{pmatrix} + \underbrace{\begin{pmatrix} d & -d \\ -d & d \end{pmatrix}}_{\text{Damping matrix}} \begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \end{pmatrix} + \underbrace{\begin{pmatrix} c & -c \\ -c & c \end{pmatrix}}_{\text{Stiffness matrix}} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} c \cdot l_0 \\ -c \cdot l_0 \end{pmatrix}$$

- With $f := \begin{pmatrix} f_1 \\ f_2 \end{pmatrix} + \begin{pmatrix} -c \cdot l_0 \\ c \cdot l_0 \end{pmatrix} \Longrightarrow \boxed{M\ddot{x} + D\dot{x} + Sx = f}$

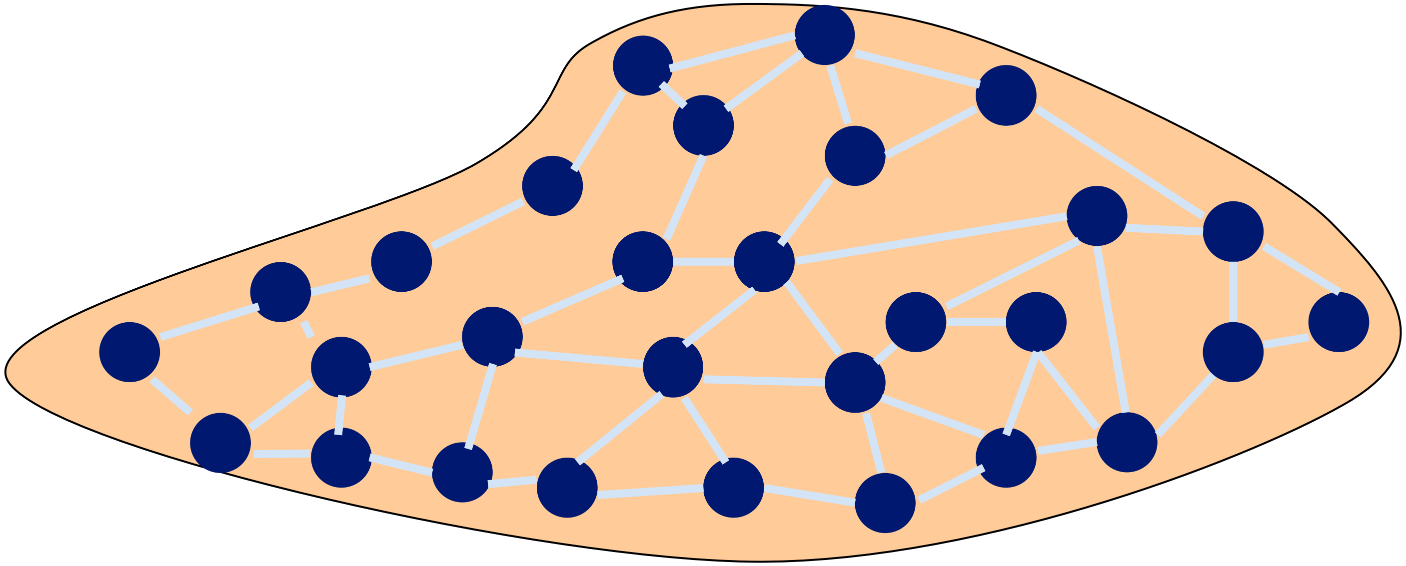
- → System of linear differential equations

Nodal Networks

Discretization of continuous soft-tissue

Definition: A nodal network model consists of

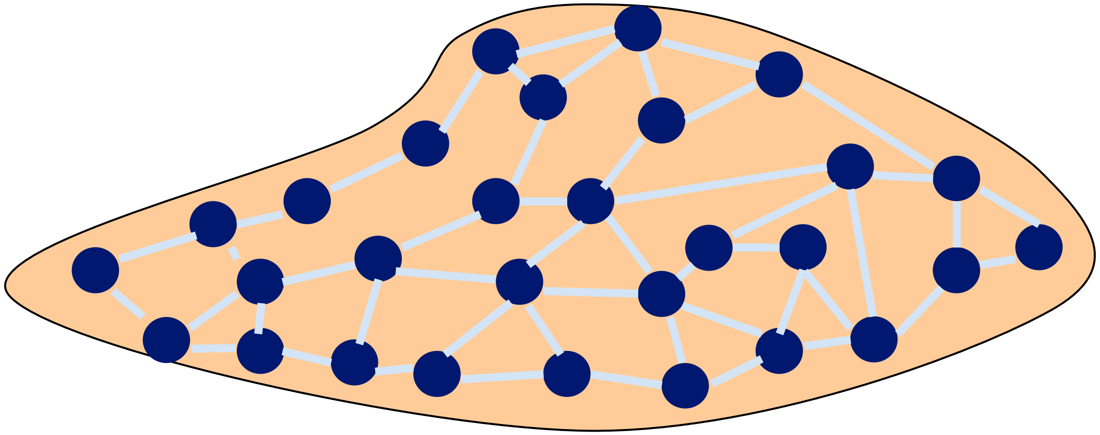
- a set P of Mass points
- a set V of connecting elements



A connecting element is described through its force function

Nodal Networks out of Mass-Spring Systems

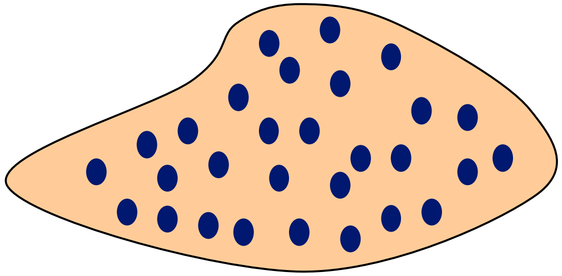
- Networks of springs and dampers are mathematically simple (System of common differential equations)
- Given: Soft-tissue structure, e.g. liver
- Wanted: Nodal Network, which approximates the deformation properties



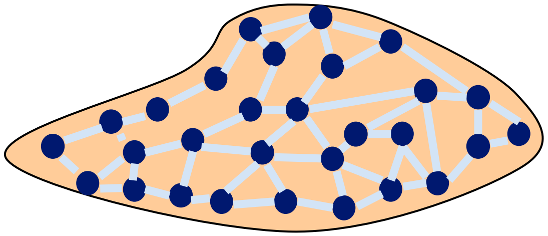
Nodal Networks

Problems:

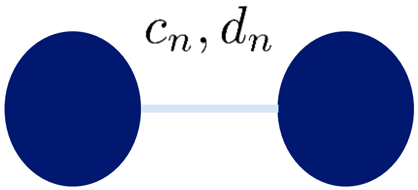
1. How should the mass points P be distributed?



2. How should the mass points be connected?



3. What values should be chosen for the parameters?



Distribution of mass point I

Wanted is the nodal approximation of a body K

Parameters:

- Number of mass points n
- Setting of point positions
- Determining mass distribution

Requirements

1. The surface points S(k) should be part of the generated set of points

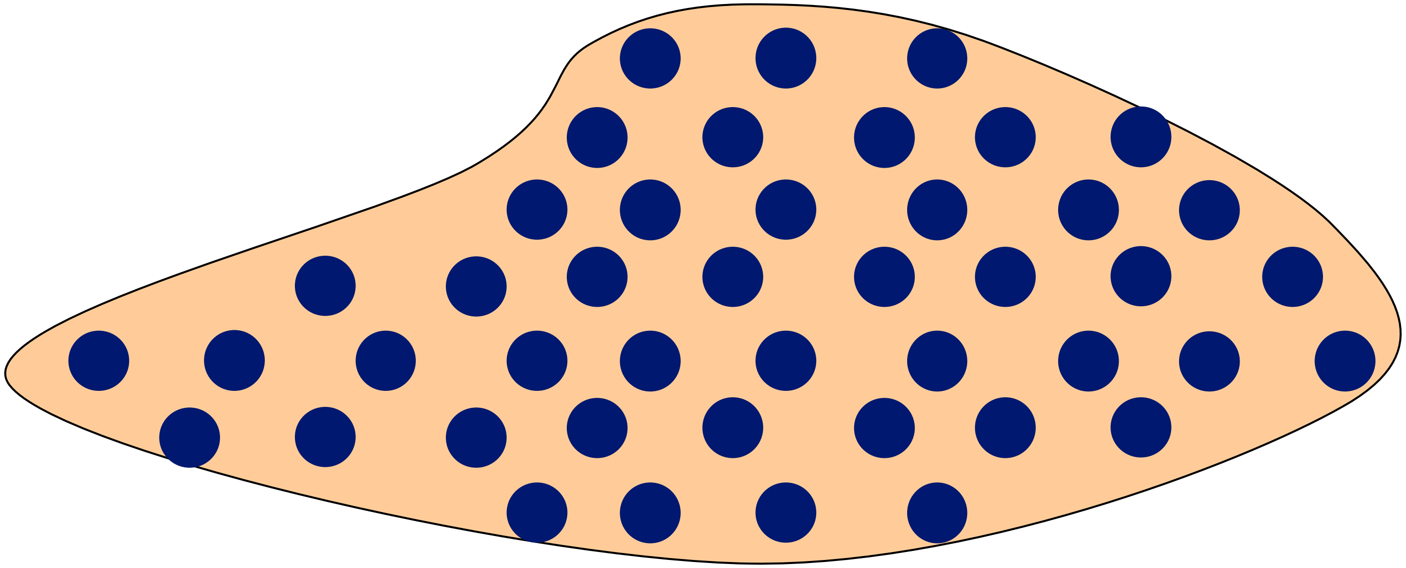
2. The points should be positioned in such a manner that they (together with the connecting elements) represent the elasticity function in an appropriate manner

3. A approximation of the mass distribution of K should be reached through discrete masses

Distribution of mass point II

Approach: Regular point distribution

- Quadratic grid
- Quadratic grid with waypoints

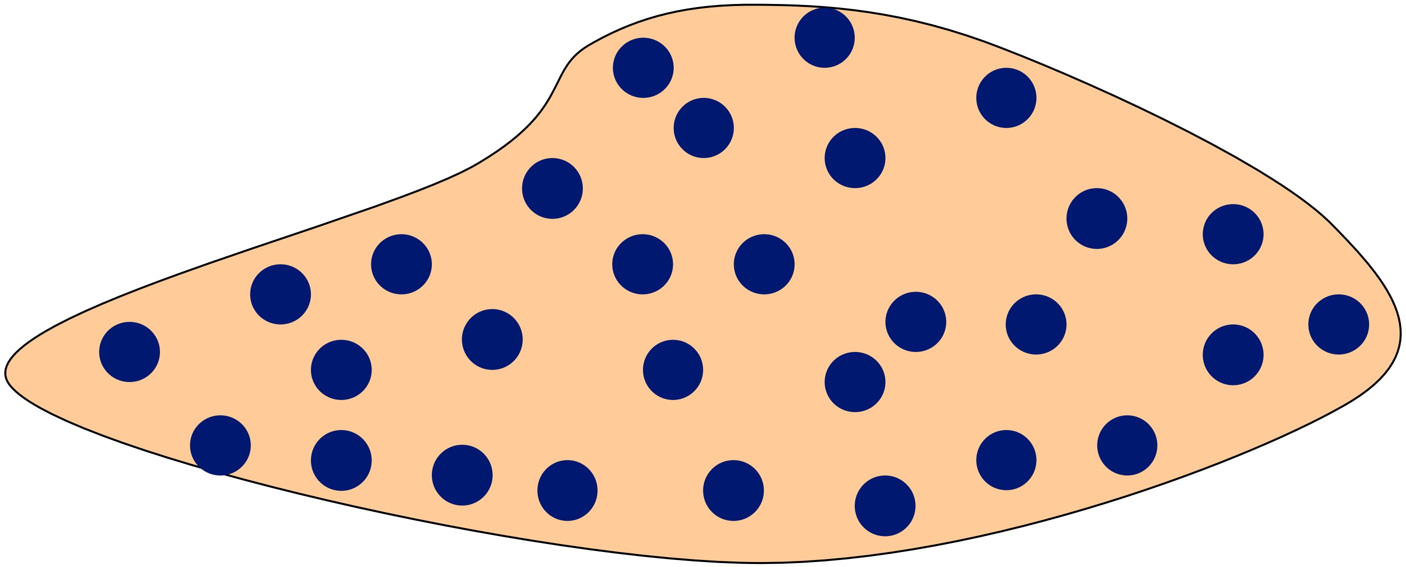


Problems:

- Can result in preferred directions (anisotropic behavior)
- Better: Random point distribution

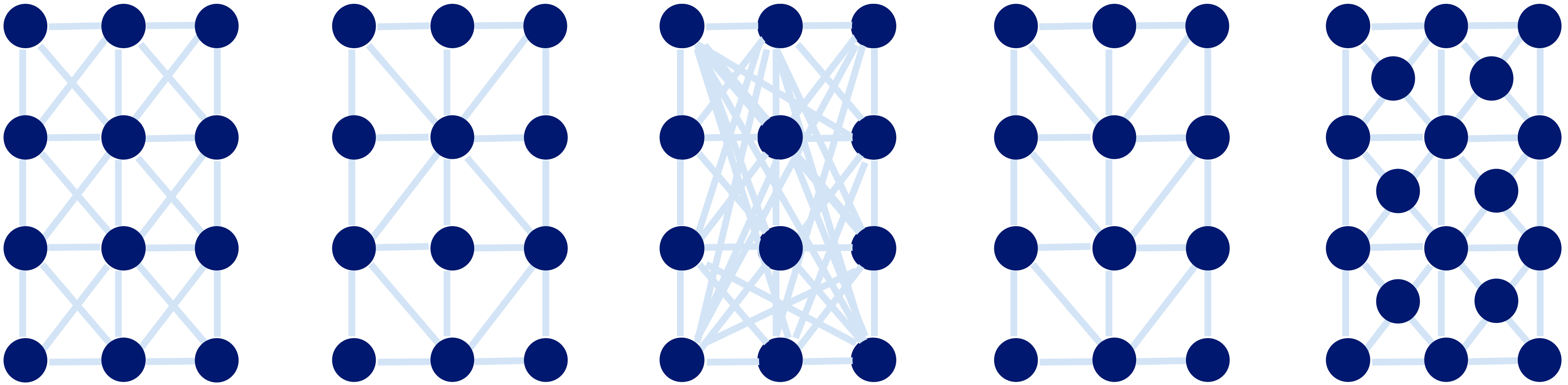
Distribution of mass point III

- Distribution of points through a stochastic process.
- Post-processing to approximate equal distances between mass points.



Connection topology with regular distribution

- How should the points be connected (Topology of the network)?
- Many combinations possible
- Try: different topologies for a quadratic grid



- 1: Topology of choice!
- 2, 4: Problems of stability
- 3: Many connection, difficult to optimize, long computation time
- 5: Better than 1, but more mass points (longer computation time)

Network topology for stochastic point distribution

Voronoi Diagram (1. Step)

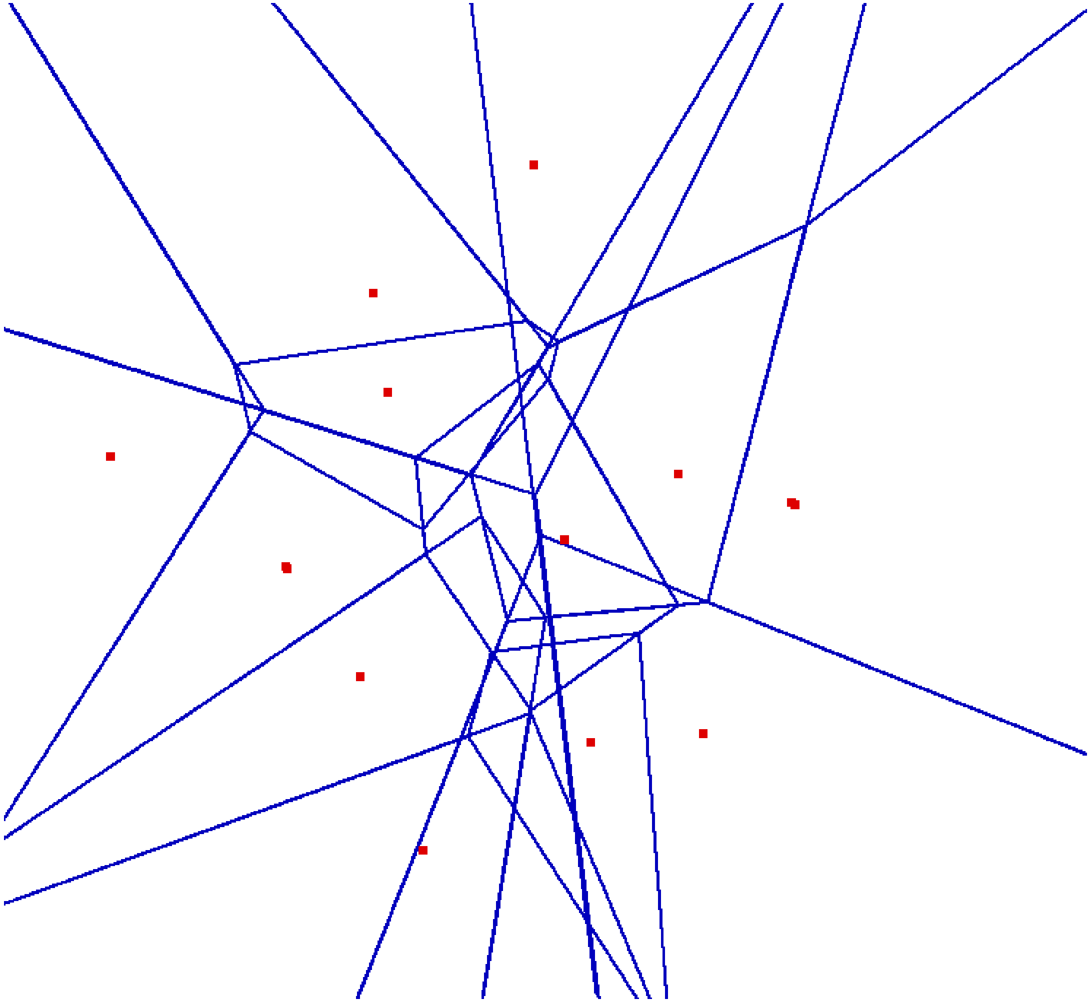
- The Voronoi diagram assigns each point p_i of a point set P to a cell, in which all points are closer to point p_i than to any other point in P
- The set of all points that are equidistant from more than one point in P form the edges of the Voronoi diagram.

Delauney Triangulation (2. Step)

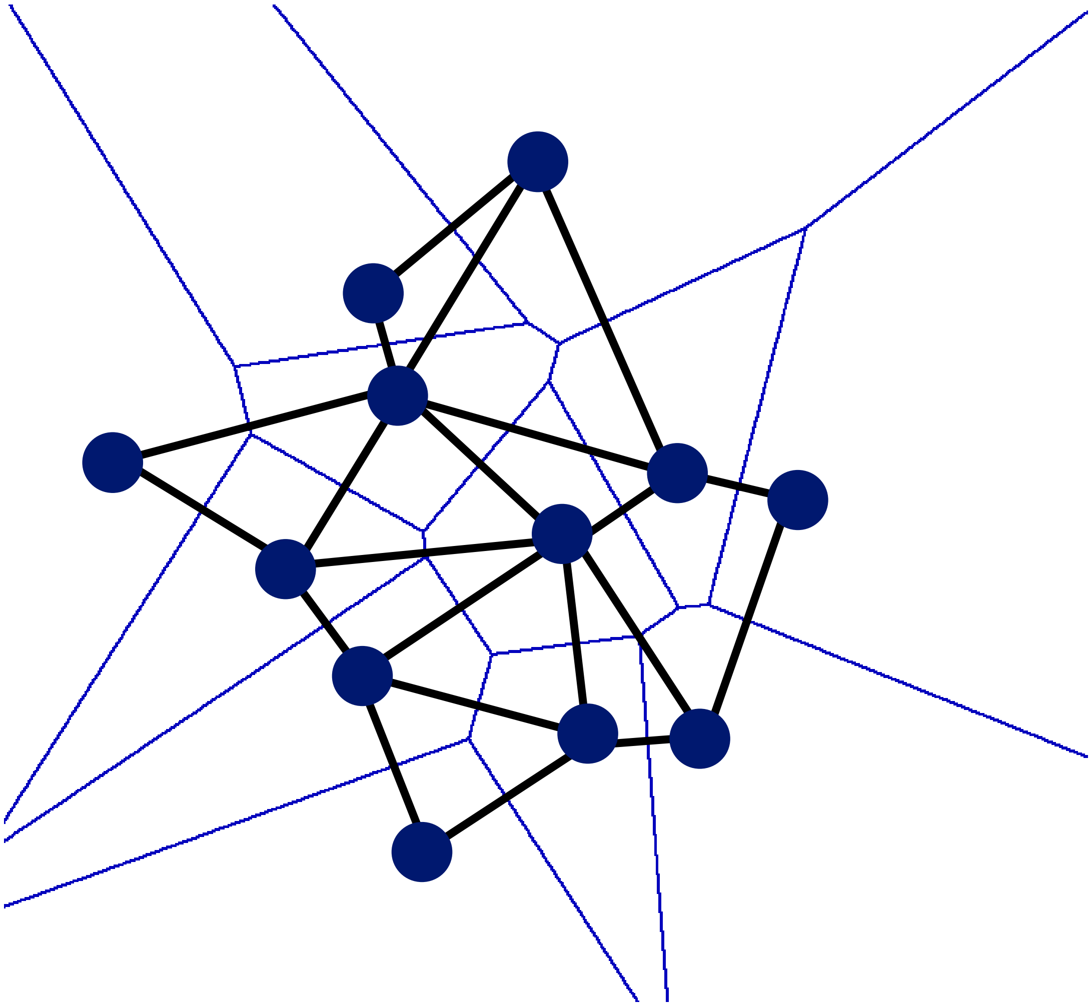
- The dual graph to the voronoi-Diagram, whose nodes are the points P and where edges between two points exist, if their Voronoi areas share a border

NCT

Voronoi Diagram

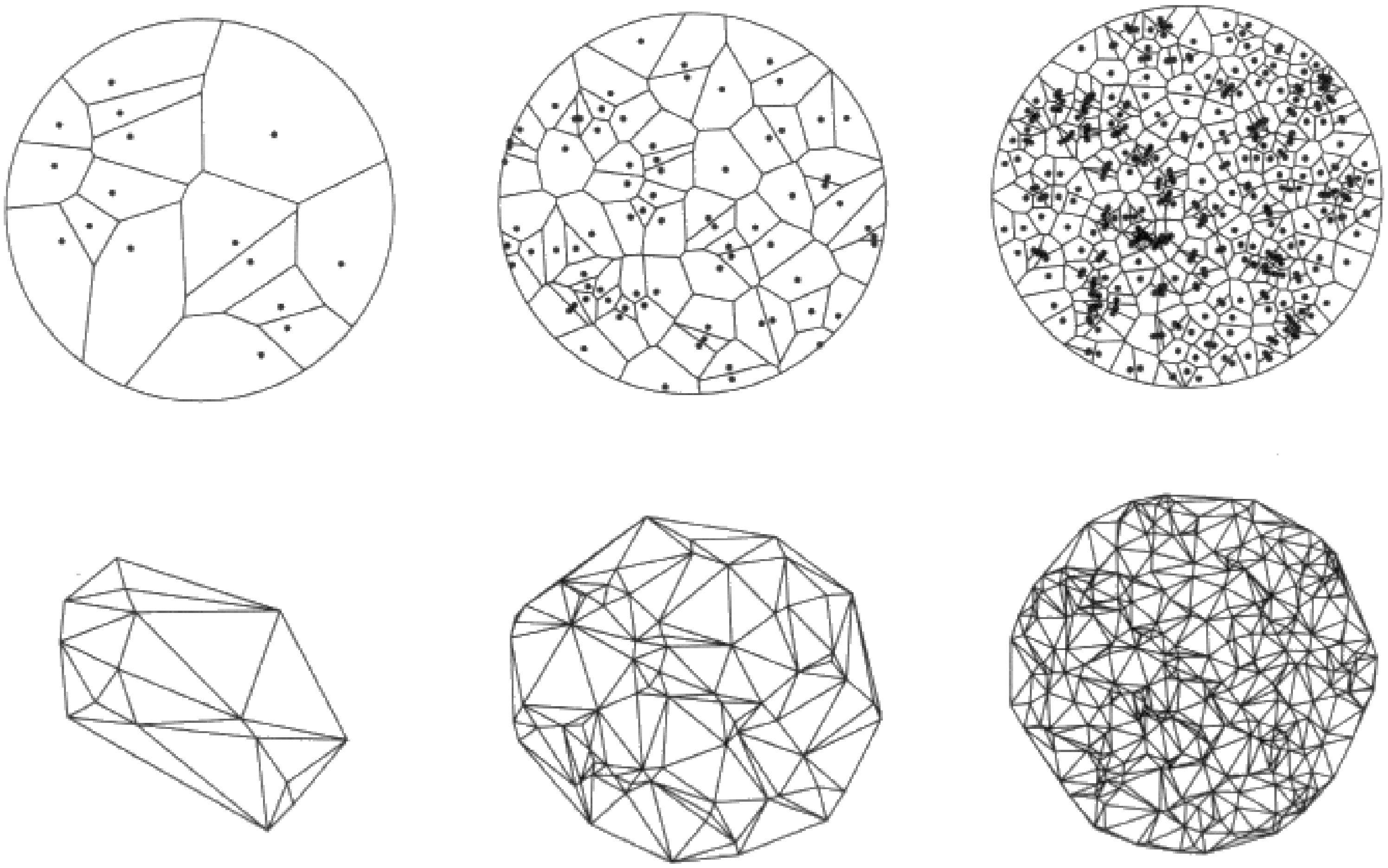


Delauney Triangulation



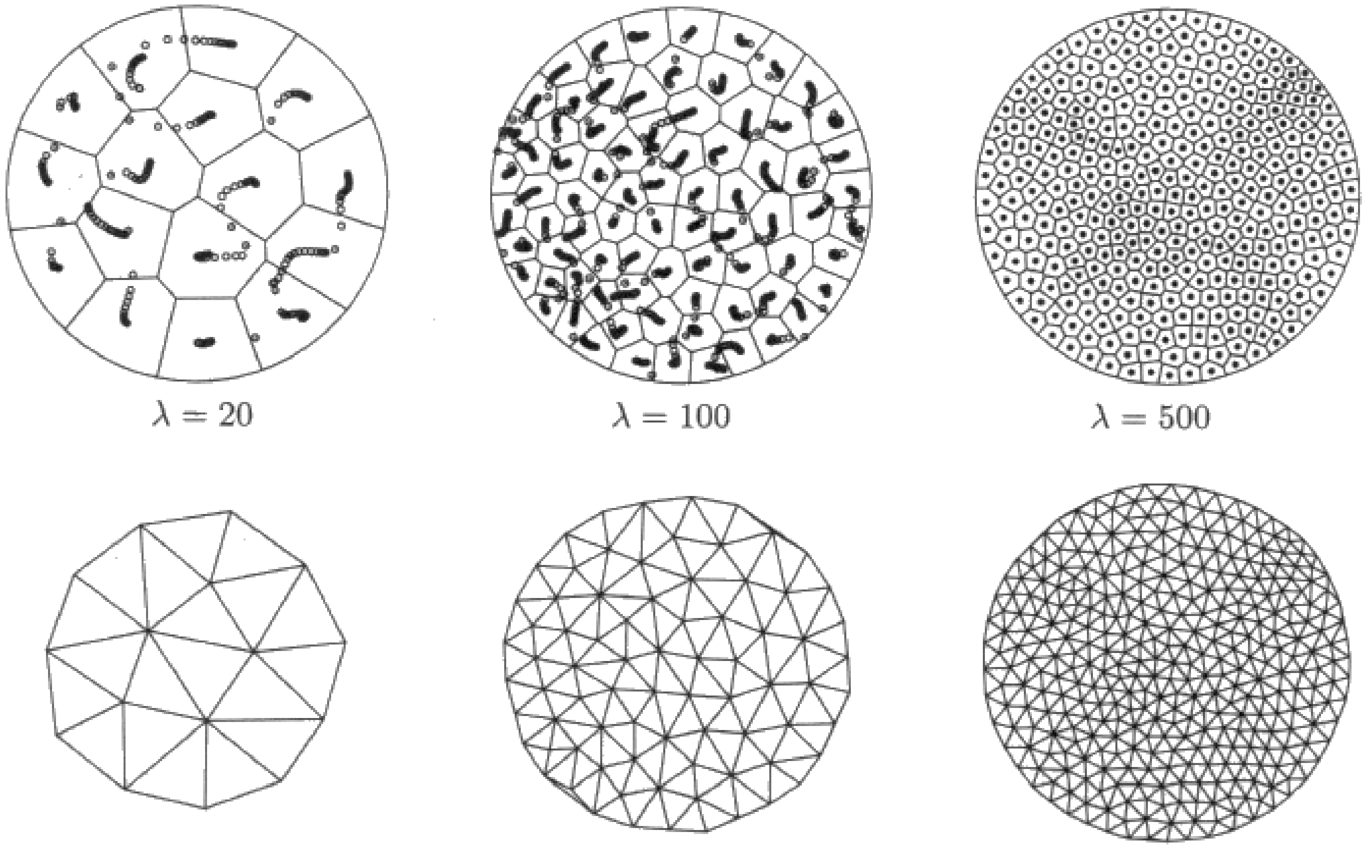
Stochastic point distribution

- Con: Very irregular grids



Stochastic point distribution

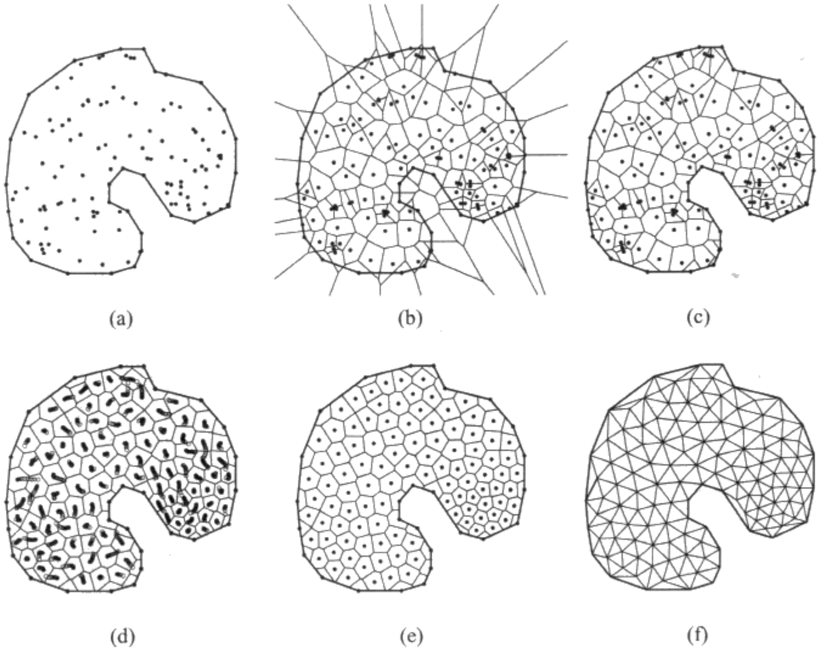
- Idea: Let points travel to the center of mass of the areas



Mass distribution

- Dynamic equivalency

  Two bodies are dynamically equivalent, if they are geometrically equivalent and if they react identically if forces and moments are applied to the same point



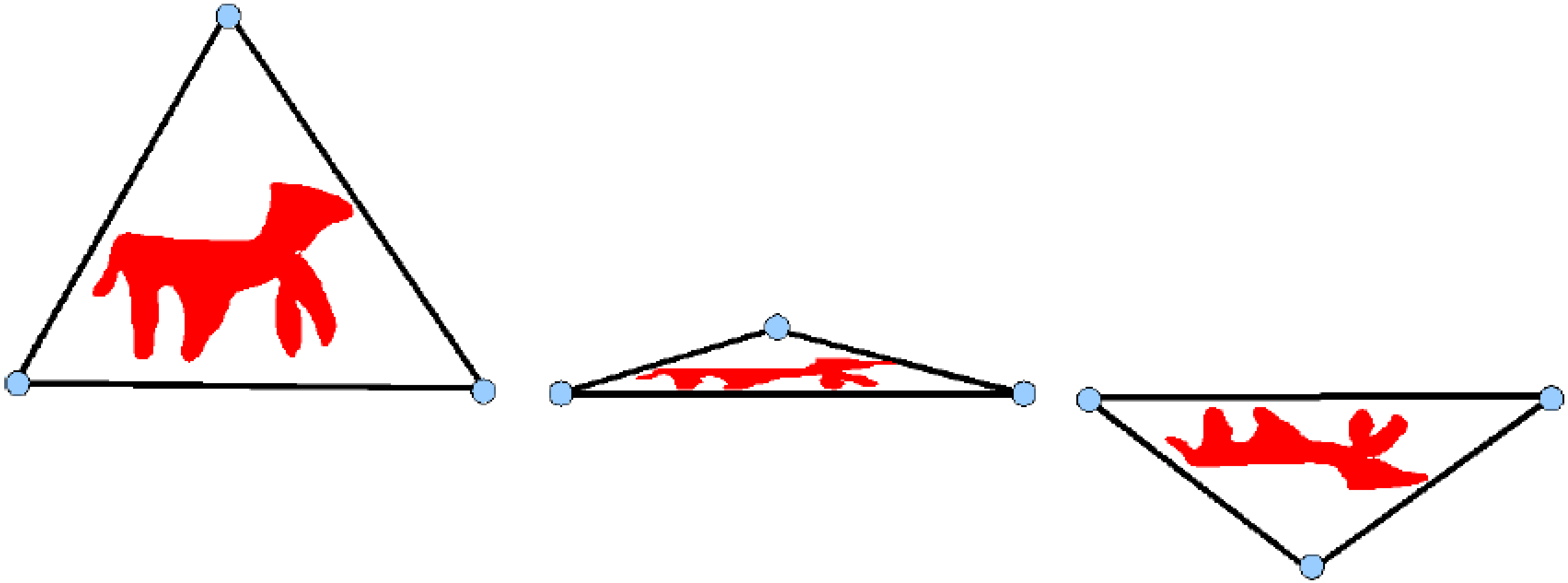
Discrete mass distribution has to approximate the mass distribution of body K well!

Parameter tuning

- Wanted:
  Parameters c_n, d_n , so that the dynamic properties of the elastic mass-point system approximate the elasticity function
- Approach:
  - Start values of the parameters to be optimized (usually spring constants) are selected via heuristics
  - Gradually change the start configuration and compute the quality of the system behavior using a cost function
  - Utilize optimization algorithms (Gradient descent,…)
- Required: Reference deformations
  - E.g. approximation through more exact method (e.g. FEM)

Problems

- Adapting the parameters to the behavior of the material is difficult
- Changes in mass distribution or topology requires parameter adjustment
- Can result in unrealistic behavior of material: Loss of volume, Inversion



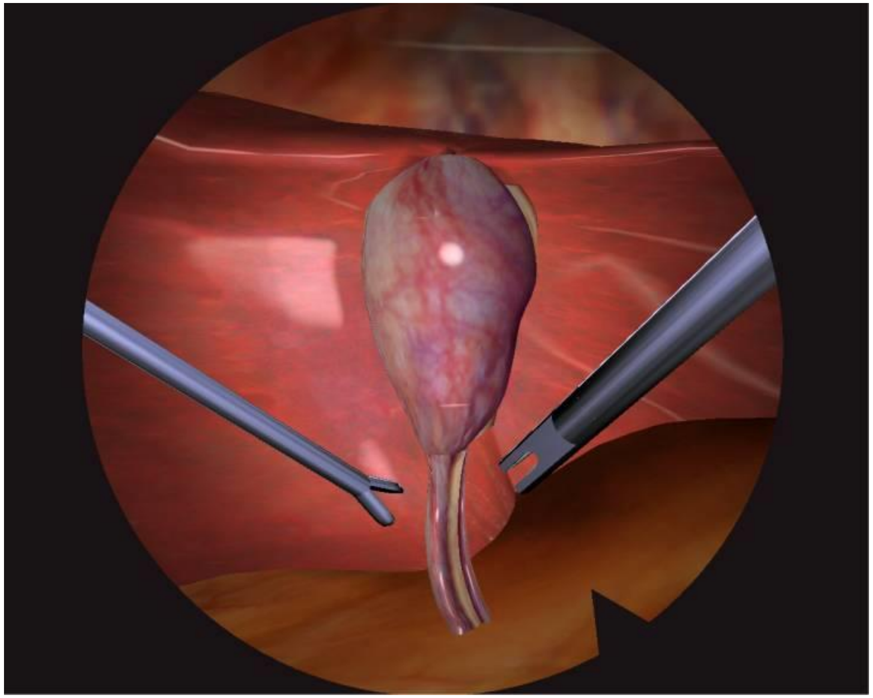
Nodal Networks – Evaluation

- Phenomenological model of behavior
- Real-time capable
- Problem Topology
  - Number and distribution of mass / connections
- Correctness of deformation
  - Often only given for small deformations, as not comparable with biomechanical conditions
- Search for correct parameters is expensive and difficult
- Unrealistic material behavior is possible

Karlsruhe Endoscopy Trainer

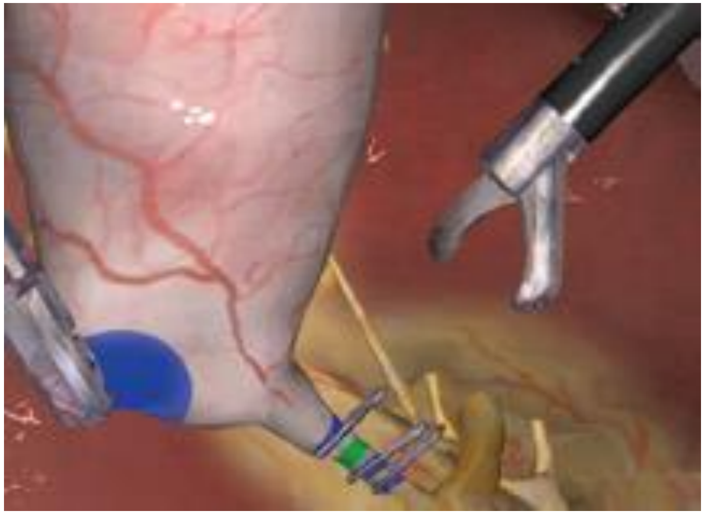
- Simulator for laparoscopic surgery
- Soft-tissue deformation with nodal networks

[FZK KA]



LAP Mentor from Simbionix

- State of the Art System
- Nodal Networks
- Improved visualizations
- Evaluation of surgical skills
- Price ca. $ 90.000 (2004)



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