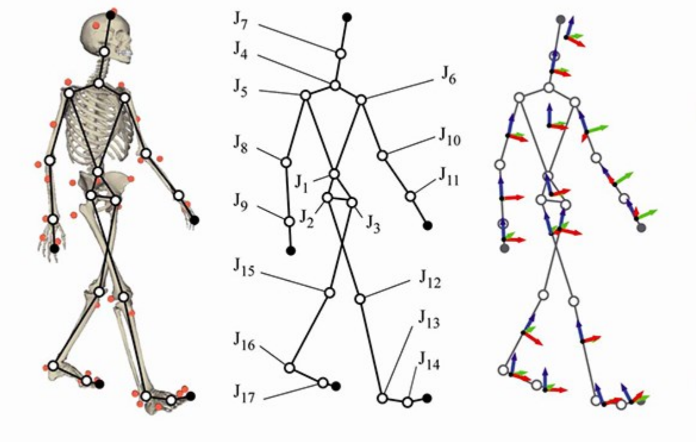
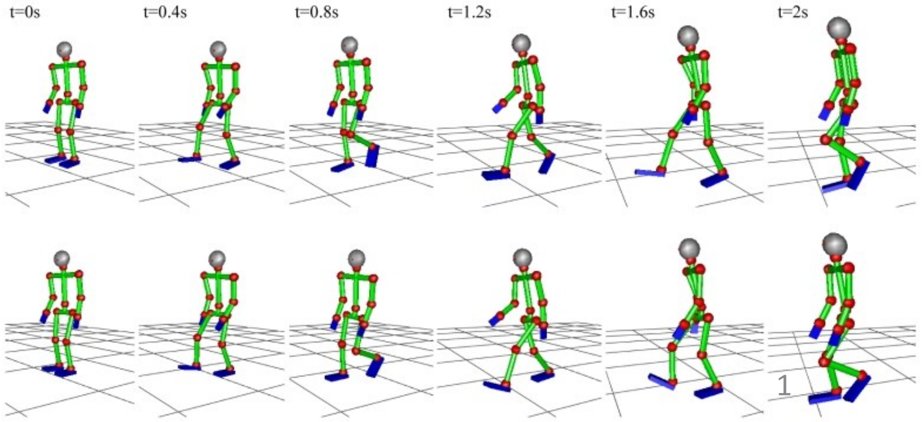
Biomechanical Analysis of Human Movement



Samet Çıklaçandır

İZMİR KÂTİP ÇELEBİ ÜNİVERSİTESİ
2010



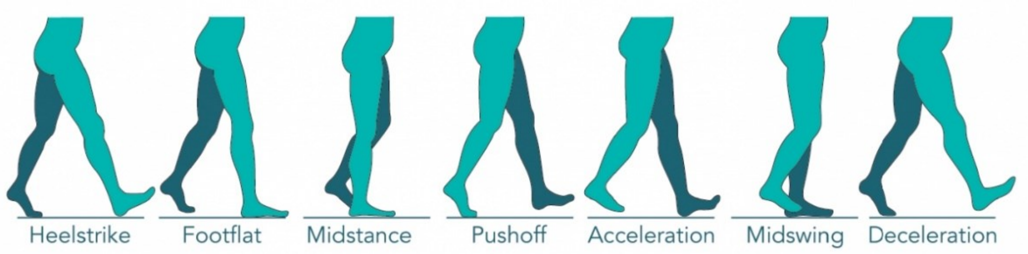
Overview

- Gait Analysis
- Data Analysis Techniques
  - Motion Capture Technologies
- Gait Cycle
- Gait Pathologies
- Gait Features
- Artificial Intelligence Techniques in Gait Analysis

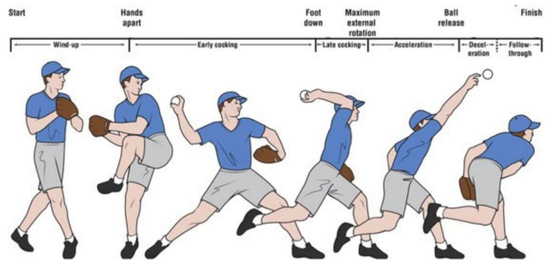
Gait Analysis

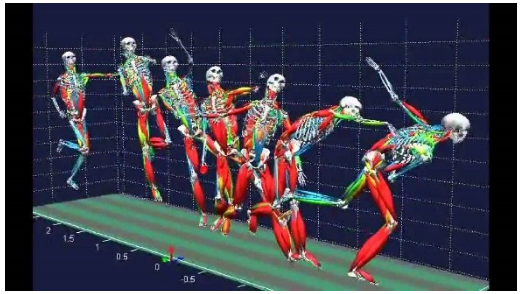
- Gait analysis is the systematic measurement, description, and assessment of those quantities thought to characterize human locomotion.
- Through gait analysis, kinematic and kinetic data are acquired and analysed to provide information which describes fundamental gait characteristics and which is ultimately interpreted by the clinician(s) to form an assessment.
- In the past, gait-related diseases were diagnosed with human observing. With the development of technology, gait analysis is performed with sensitive devices.

Objective

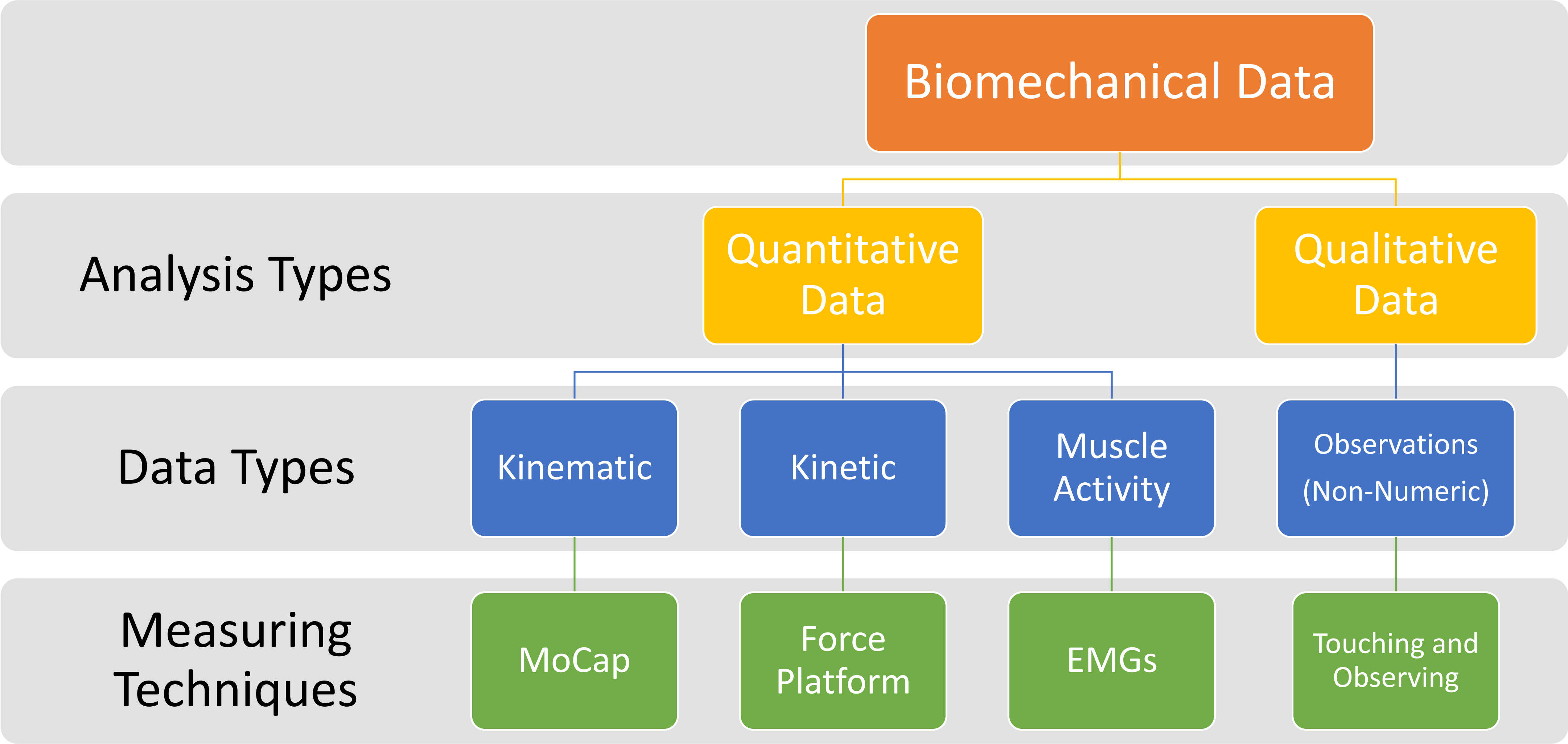


- Analyzing human movements
- Measure angles between the limbs
- Sports Biomechanics (Sports Performance)
- Kinematic data collection
- Kinetics data calculation with software
- Load distributions on joints, Implant designs
- Ergonometric designs





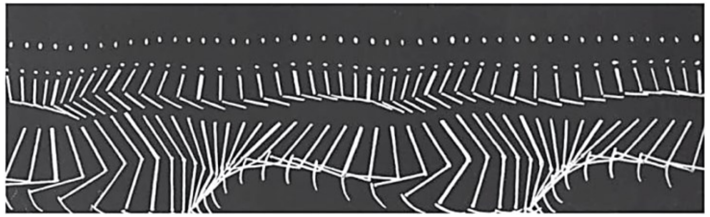
Data Analysis Techniques in Human Movement



Motion Capture Technologies

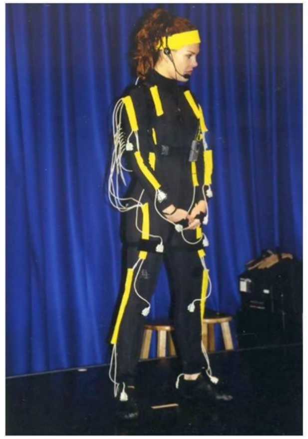
- Motion Capture (MOCAP) is sampling and recording motion of humans, animals and inanimate objects as 3d data for analysis, playback and remapping
- Performance capture is acting with motion capture in film and games,
- Military and medical research purposes
- The idea of motion capture was first put forward by Eadweard Muybridge in 1877 (Zoopraxiscope).
- Etienne-Jules Marey collected the movement data with the MOCAP suit that was developed in the same years.

Zoopraxiscope



MOCAP suit

Optoelectronic Measurement Systems (OMSs)



Electromagnetic Measurement Systems (EMSs)

MOCAP Methods

Inertial Sensory Systems (IMUs)

Image Processing Systems (IMSs)

Ultrasonic Localization Systems (UMSs)

Optoelectronic Measurement Systems (OMSs)

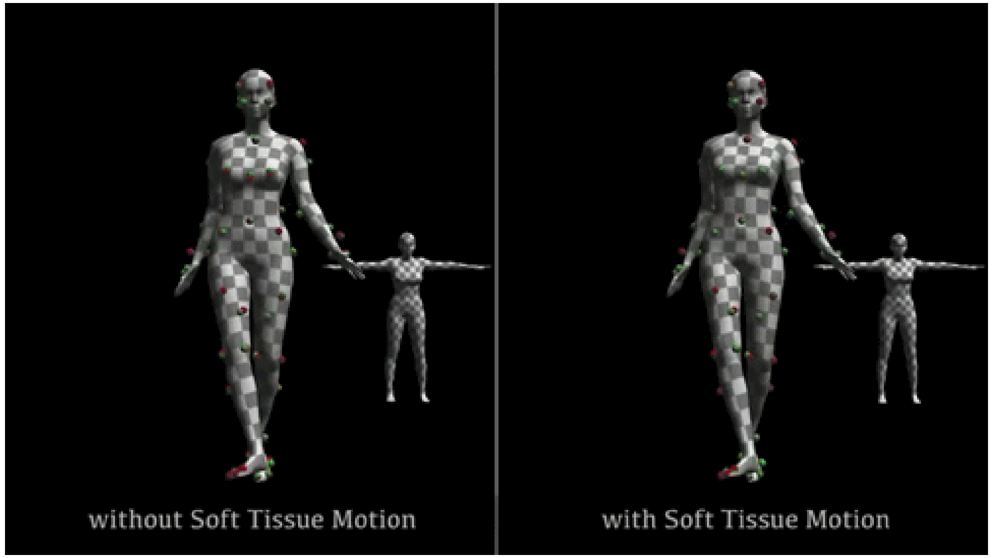
- Reflective markers
- Active and Passive Marker
- Up to 5000fps, under 1mm accuracy
- Gold Standard in motion capture
- Pros
  - Very accurate
- Cons
  - Bound to restricted area
  - Line-of-sight necessary
  - Highly sensitive for shift (disturbances) of cameras
  - Sunlight interferes measurements

Electromagnetic Measurement Systems (EMSs)

- Electromagnetic sensors placed on joints or other critical points
- Measures orientation and position of sensor relative to electromagnetic field generated by the transmitter
- Pros
    - Large volumes
    - No-line-of-sight necessary
- Cons
    - Less accurate than OMS
    - Sensitive to ferromagnetic disturbances
    - Noise progressive to distance from base station
    - Low sample frequency

Image Processing Systems (IMSs)

- In image processing captured films or photos are digitally analyzed.
- No marker, No sensor
- Computer Vision Algorithms
- High-speed cameras



- Pros
  - Better accuracy than EMS
  - Improved range compared to OMS
  - Markerless tracking possible
- Cons
  - Currently outperformed by EMS, OMS
  - Requires self-development

Inertial Sensory Systems (IMUs)

- Inertial trackers placed on joints
- Measures orientation and position with accelerometers, gyroscopes, magnetometers on each segment
- Pros
  - Minimally invasive
  - Large volume
- Cons
  - Cannot measure position stand-alone
  - Dependent on fusion filter

ROKOKO, KINECT, OPTITRACK Systems

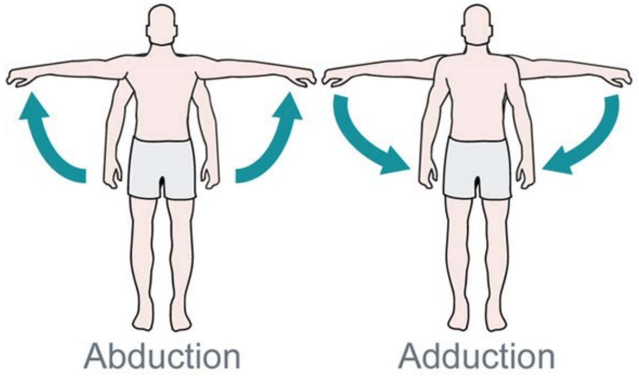
Table 1 Comparison of ROKOKO, KINECT and OPTITRACK systems

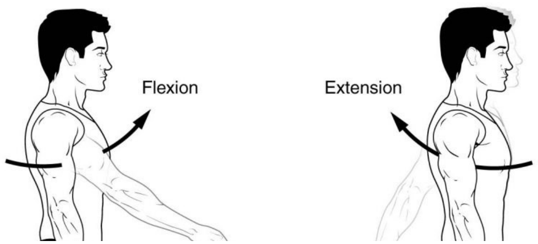
	ROKOKO	KINECT	OPTITRACK	XSENS
Sample Rate	100 FPS	30 FPS	120 FPS	120FPS
Sensor	19	-	-	3
Camera	-	2	6	-
Connections	WIFI	USB	USB	WIFI
Latency	-	-	10ms	20ms
Price	1250£	399$	999-5999 per camera	3600$

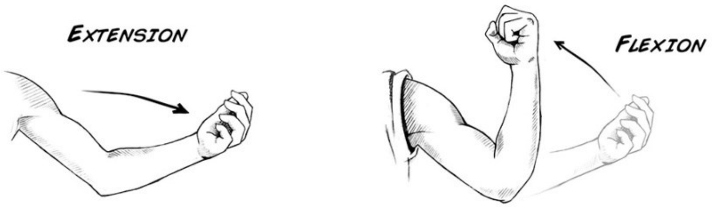
Movements

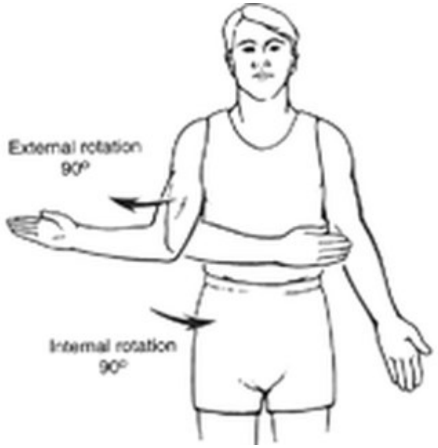
- Abduction-Adduction
- Flexion-Extension
- Internal-External Rotation
- Fugl Meyer
- Coronal, Sagittal and

Transverse planes



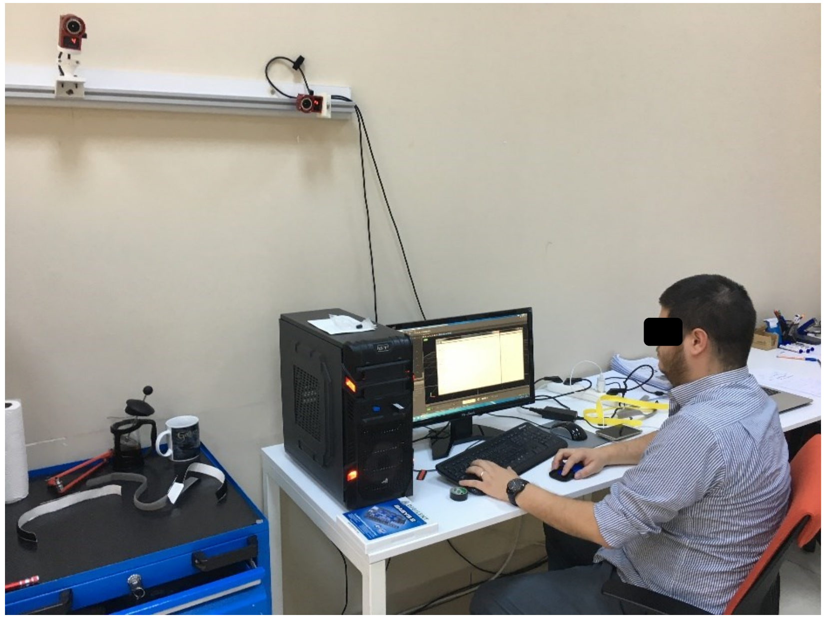






Rokoko Mocap Suit and Xsens Motion Tracker

Demonstration of movements to subjects

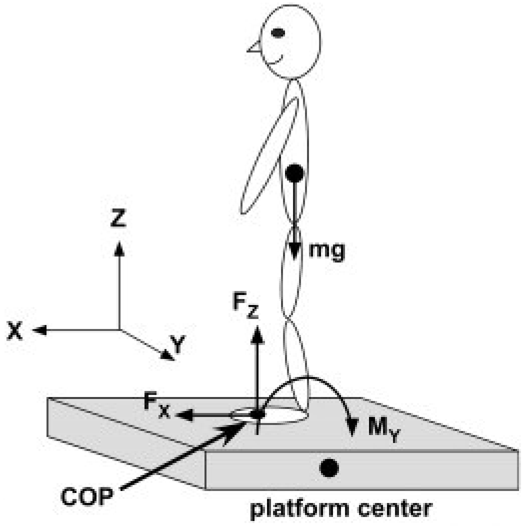


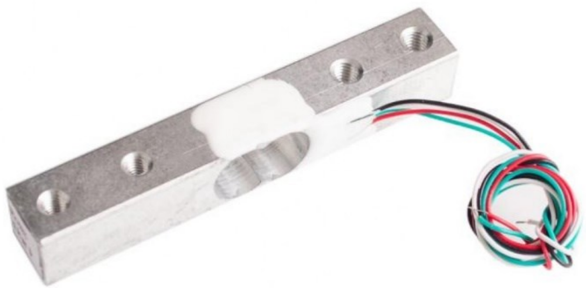
OPTITRACK System

Force Platform / Plates

- Force plates are tools used for the measurement of ground reaction forces **(GRF)** during walking, jumping, or any other type of movement.
  - Vertical force
  - Shear Force
  - Lateral and horizontal forces.
- Load cells (Newton)

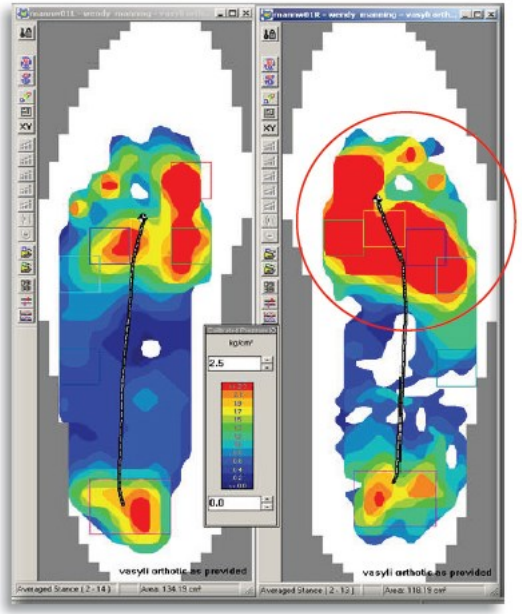
•Velocity (m/s)
•Power (Watts)
•Displacement (Meters)
•Temporal parameters (seconds)
•Left/Right Asymmetry

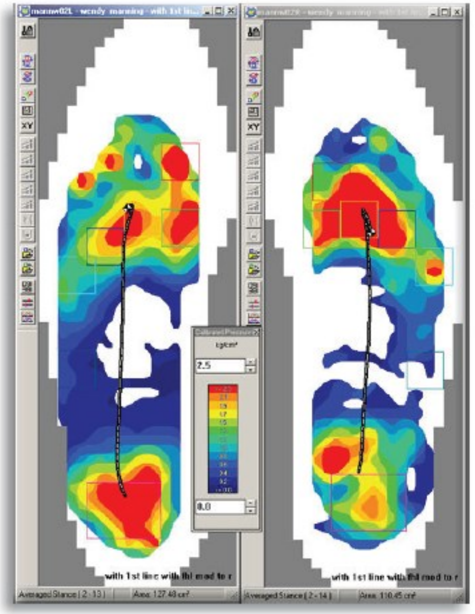


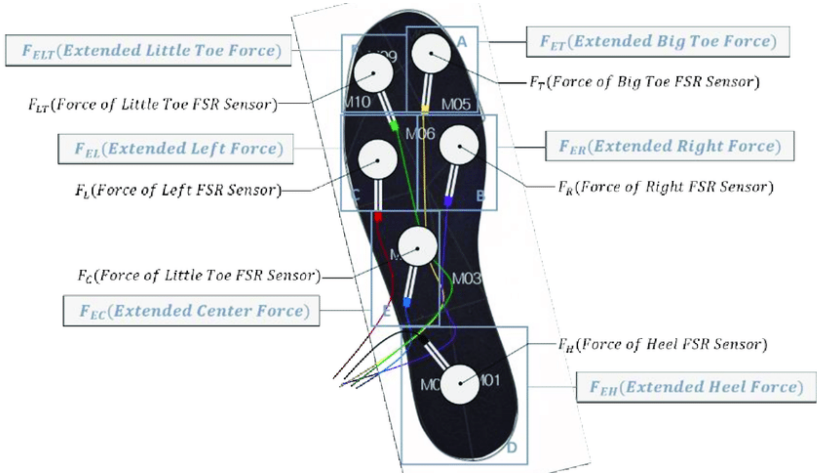


Insole Pressure Sensor

- It provides a topographical image of pressure variation across the contact area.
- Foot pressure distribution
- Force sensitive resistors (FSR)

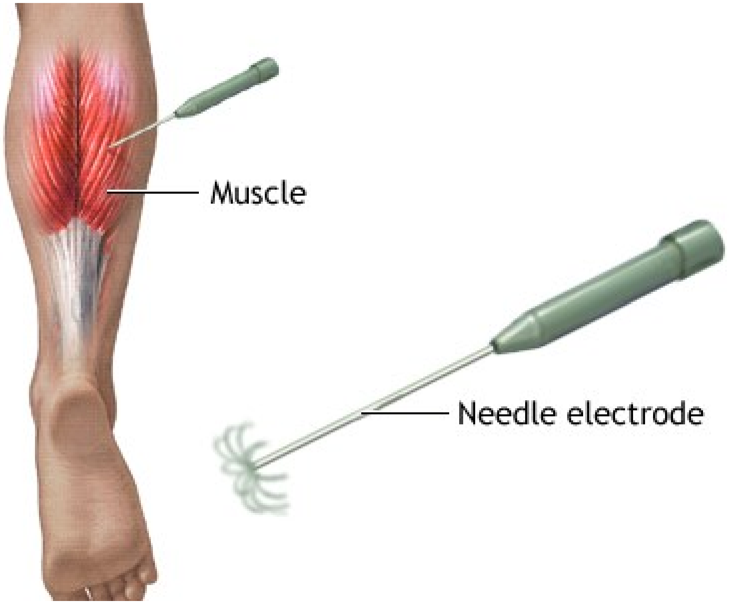


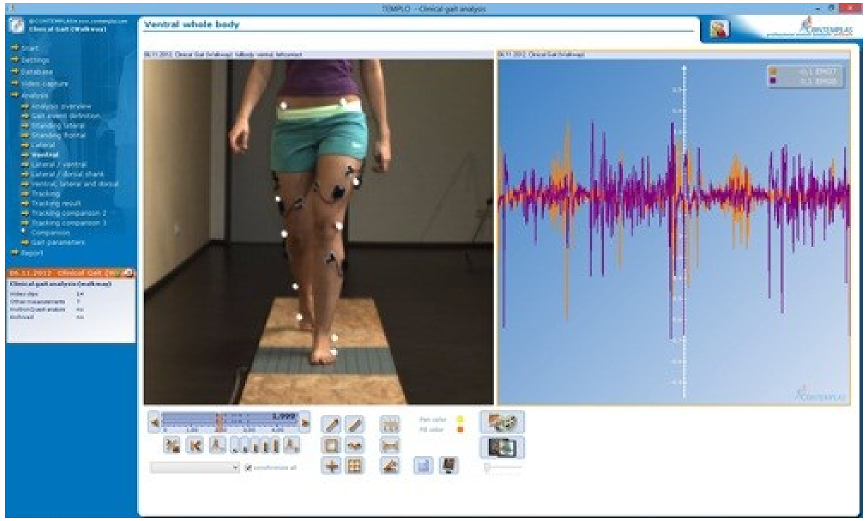




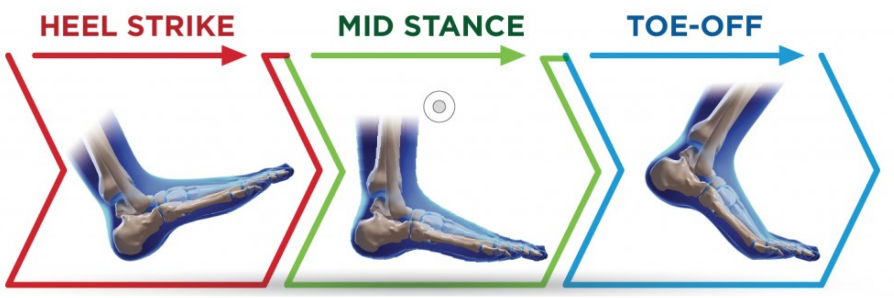
Electromyography (EMG)

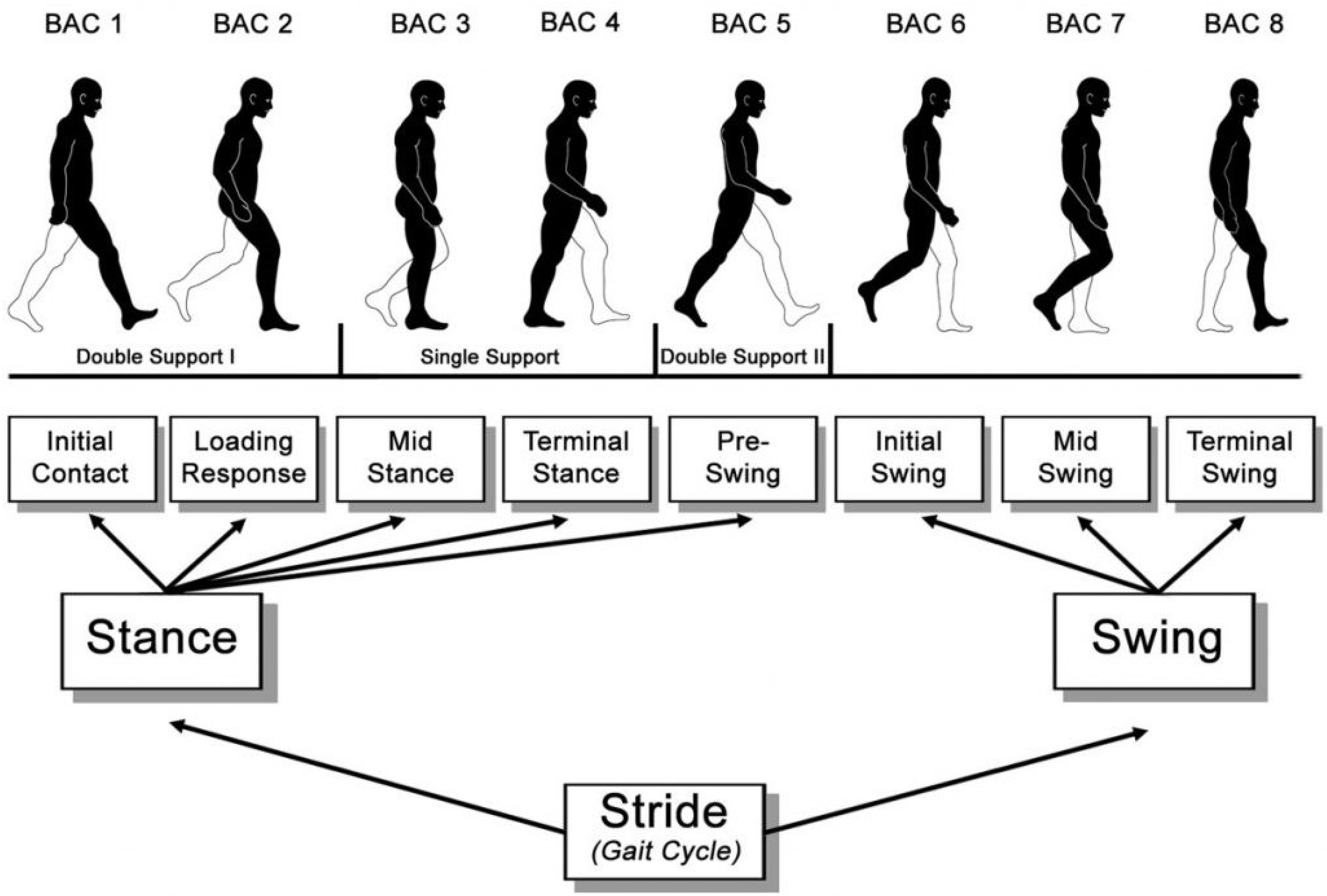
- It is a diagnostic procedure to assess the health of muscles and the nerve cells that control motor neurons. EMG results can reveal nerve dysfunction, muscle dysfunction or problems with nerve-to-muscle signal transmission.





Gait Cycle

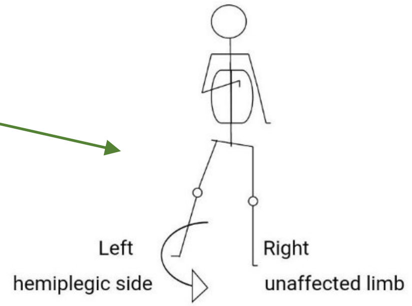


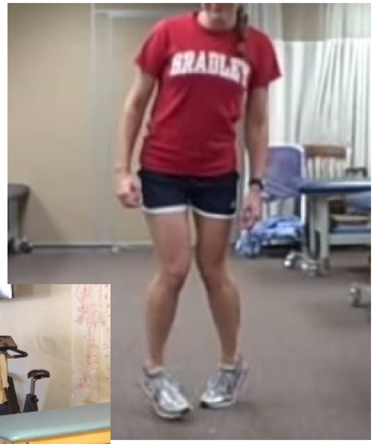


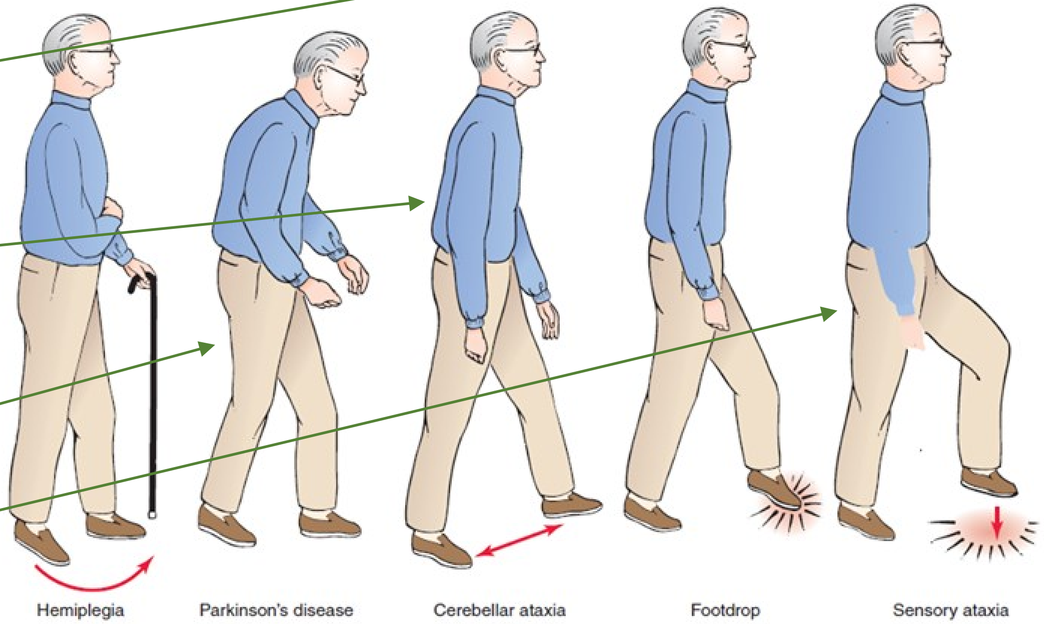
- **Gait cycle** is the time between successive foot contacts of the same limbs. Thus, one gait cycle begins when the reference foot contacts the ground and ends with subsequent floor contact of the same foot.

Gait Abnormalities

- Hemiplegic Gait
- Diplegic Gait
- Neuropathic Gait
- Myopathic Gait
- Choreiform Gait (Hyperkinetic Gait)
- Ataxic Gait (Cerebellar)
- Parkinsonian Gait
- Sensory Gait



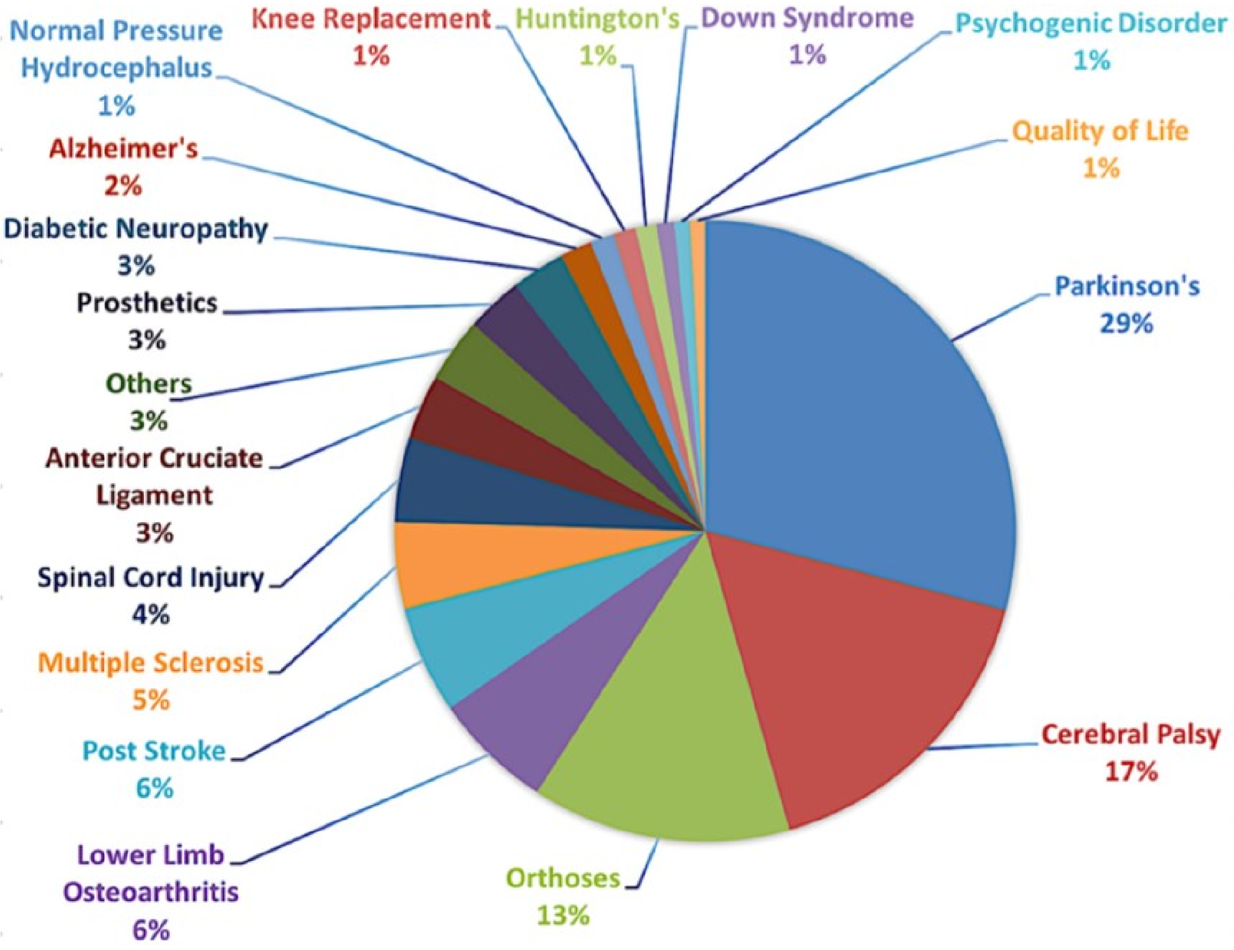




https://stanfordmedicine25.stanford.edu/the25/gait.html

Gait Pathologies

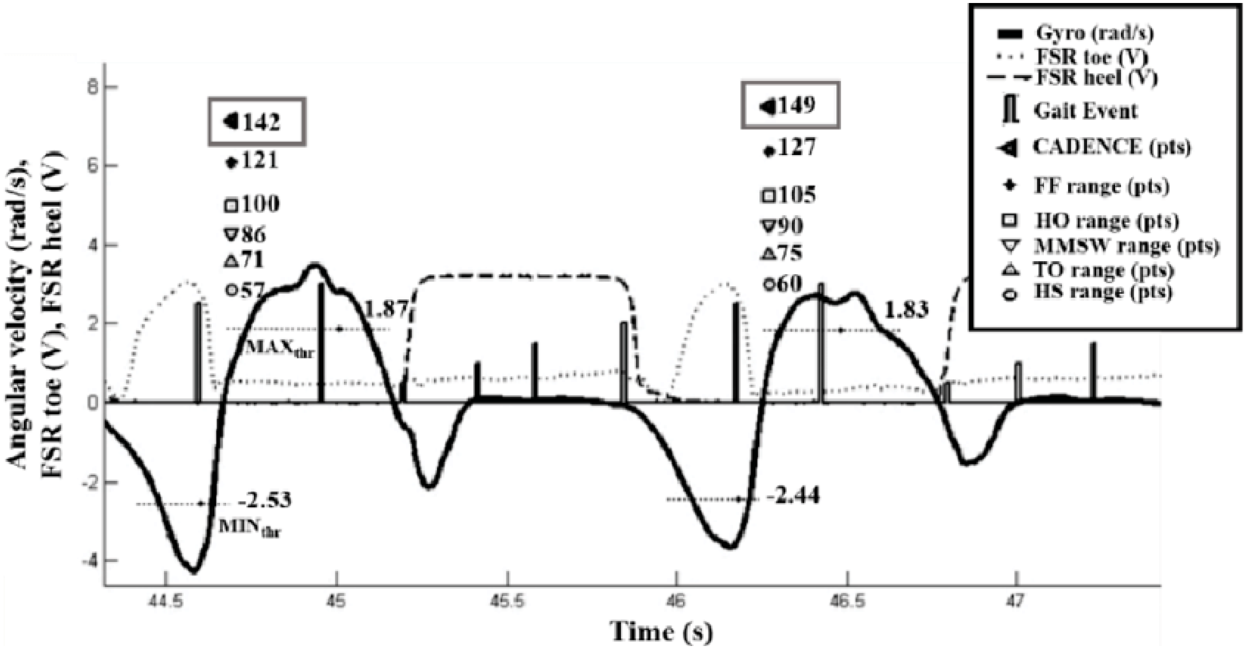
- Parkinson’s
- Cerebral Palsy
- Orthoses Design
- Lower Limb Osteoarthritis
- Stroke
- Multiple Sclerosis
- Spinal Cord Injury
- Anterior Cruciate Ligament
- Prosthetics Design
- Diabetic Neuropathy
- Alzheimer’s
- Normal Pressure Hydrocephalus
- Knee Replacement
- Huntington’s
- Down Syndrome
- Psychogenic Disorder
- Quality of Life
- Fall Risk Analysis



Gait Features and Gait Pattern

- Gait Speed
- Angular Velocity
- Vertical Position
- Joint Angles
- Cadence
- Stride Length
- Energy Cost
- Step Length-Width

- Stance time
- Swing time
- Double support time
- Moment
- Gait stability
- Gait complexity



Artificial Intelligence (AI) Techniques in Gait Analysis

- Human Activity Recognition
- Classification of pathological gait patterns
- Person identification and gender classification
- Gait event detection
- Analysis of gait pattern of the prosthetic limb
- Analysis of sports movements and design sports equipment

Gait Data Collection → Gait Feature Extraction → Neural Network Classified → Gait Class

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AI Algorithms

- Support Vector Machine (SVM)
- Hidden Markov model (HMM)
- Decision Tree
- K Nearest Neighbor (kNN)
- Naive Bayes
- Multi Layer Perceptron (MLP)

```
from sklearn.svm import SVC # "Support vector classifier"
model = SVC(kernel='linear', C=1E10)
model.fit(X, y)
```

```
>>> import numpy as np
>>> from sklearn import hmm

>>> startprob = np.array([0.6, 0.3, 0.1])
>>> transmat = np.array([[0.7, 0.2, 0.1], [0.3, 0.5, 0.2], [0.3, 0.3, 0.4]])
>>> means = np.array([[0.0, 0.0], [3.0, -3.0], [5.0, 10.0]])
>>> covars = np.tile(np.identity(2), (3, 1, 1))
>>> model = hmm.GaussianHMM(3, "full", startprob, transmat)
>>> model.means_ = means
>>> model.covars_ = covars
>>> X, Z = model.sample(100)
```

```
import numpy as np
import pandas as pd
from sklearn.metrics import confusion_matrix
from sklearn.cross_validation import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
```

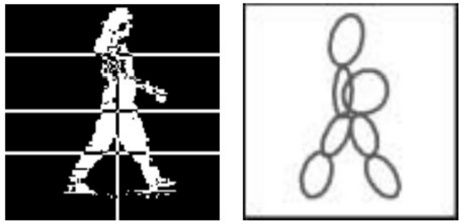
```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from sklearn.datasets import load_breast_cancer
from sklearn.metrics import confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
import seaborn as sns
sns.set()
```

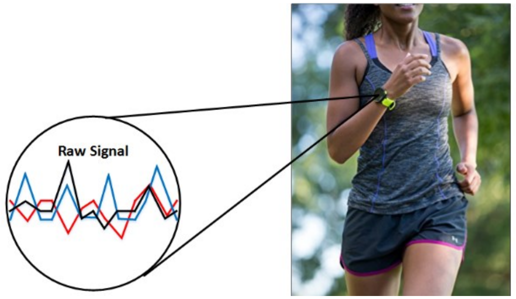
```
from sklearn.neural_network import MLPClassifier

X = [[0, 0], [1, 1]]
y = [0, 1]

# create mutli-layer perceptron classifier
clf = MLPClassifier(solver='lbfgs', alpha=1e-5,
                    hidden_layer_sizes=(5, 2), random_state=1)
```

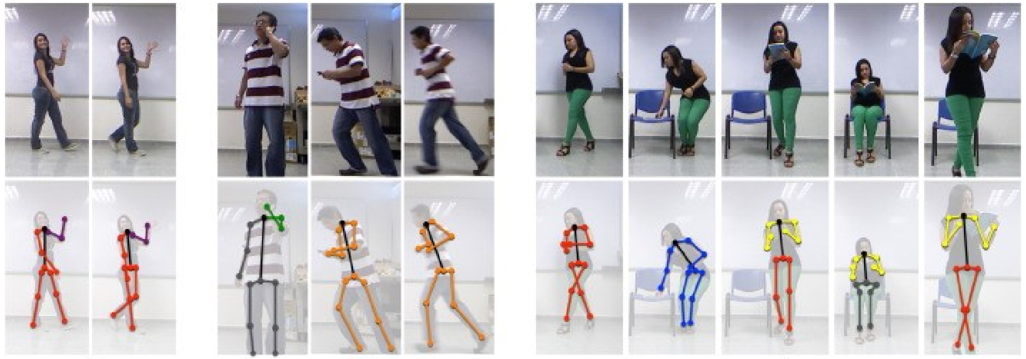
```
#Import Gaussian Naive Bayes model

from sklearn.naive_bayes import GaussianNB
```

Human Activity Recognition (HAR)

- The movements of humans are identified for eldercare, home nursing, security, fall detection, and gait analysis.
- Movements : walking, jumping, lying, climbing the stairs, etc.
- Measurement techniques: Accelerometer or Video-based (Image Processing)
- Devices: Smartwatch, Smartphone, IMU sensors and Optoelectronics







a) b) c)

Review of studies on the accelerometer

- First applications in 1999,

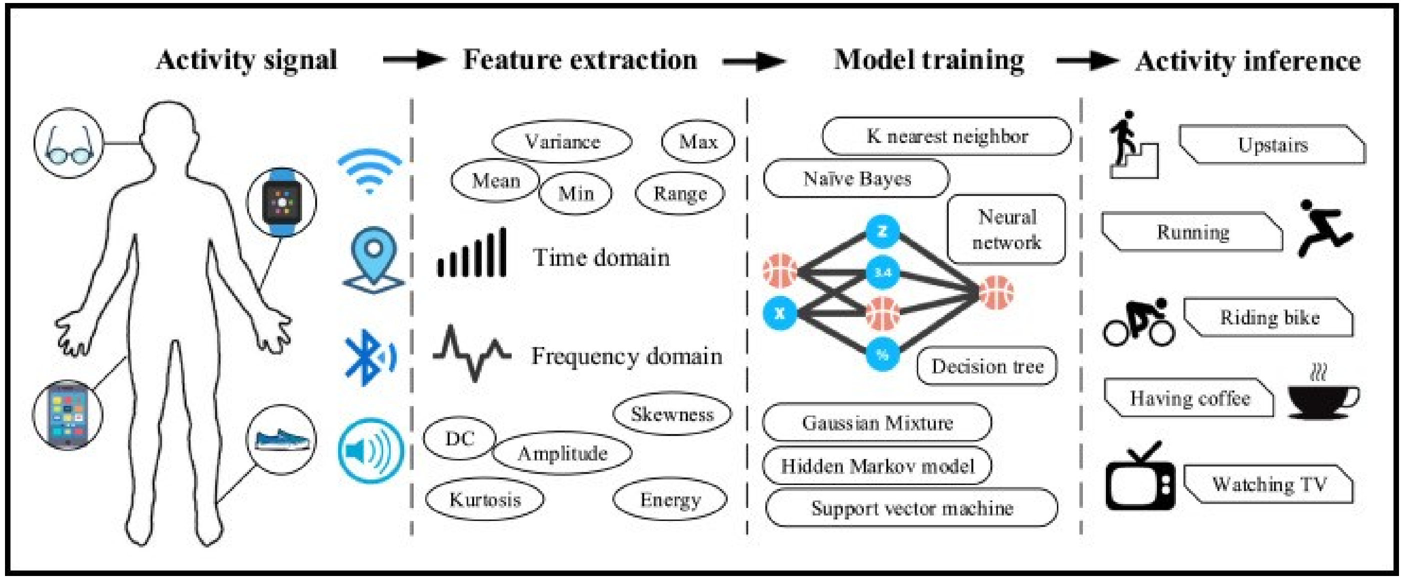
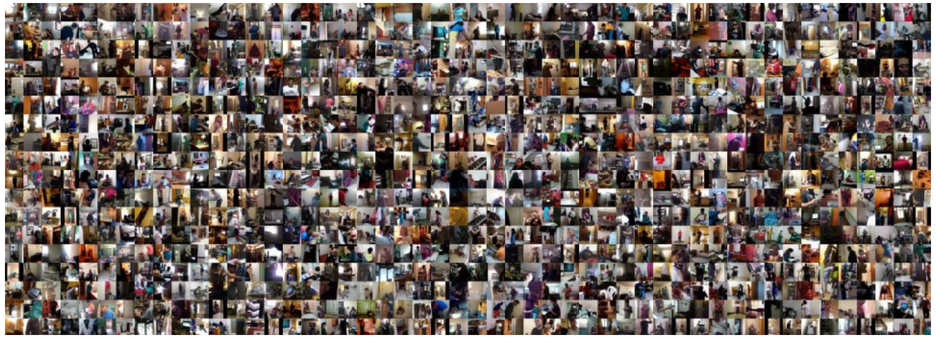


Table 1: Review of studies on the accelerometer; measurement systems and their performance with artificial intelligence techniques and classifier

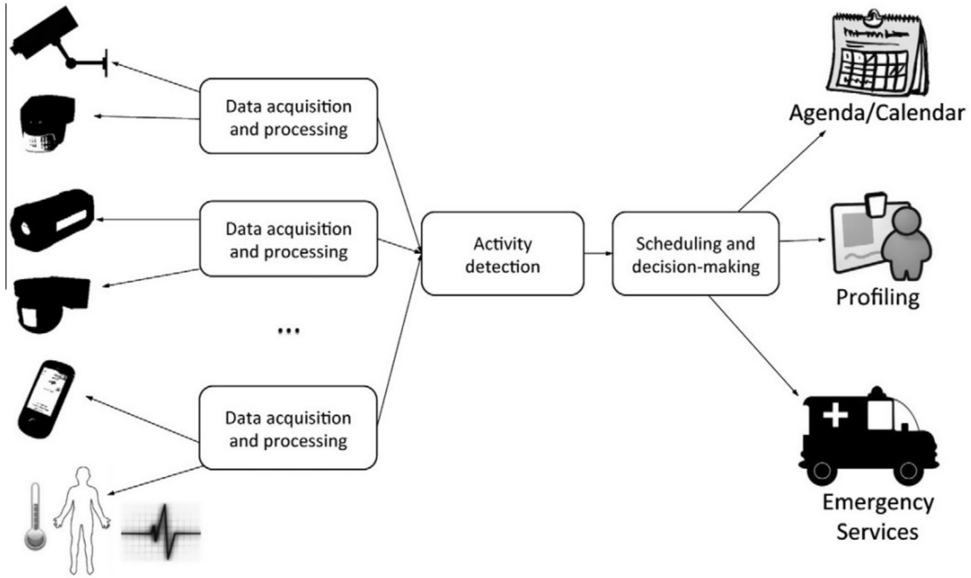
Study	System	#Subjects	Methods	Activities	Accuracy
Mathie, 2004 [13]	Waist-mounted Triaxial IMU	26 Volunteers	A Binary Decision Tree	Falling, Walking, Sitting, Standing, Lying	98.9%
Pirttikangas, 2006 [14]	The Cookie Triaxial Acc.	9 Males and 4 Females	Multilayer Perceptrons and kNN Classifiers	Typing, Watching TV, Drinking, Stairs Ascent and Descent	MLP 89.76%, kNN 92.89%
Anguita, 2012 [15]	Smartphones	30 Volunteers	Support Vector Machine (SVM)	Walking, Upstairs, Downstairs, Standing, Sitting, Laying	89.3%
He, 2009 [16]	ADXL330 Triaxial Acc.	9 Males and 2 Females	SVM	Running, Jumping, Walking, Still	97.51%
Krishnan, 2008 [17]	Acc. placed at hip	10 Random Subjects	AdaBoost, SVM, RLogReg	Walking, Sitting, Standing, Running, Bicycling, Lying Down, Climbing Stairs	Adaboost 92.81%, RLogReg 86.55%, SVM 82.28%
Leonardis et al., 2018 [18]	Tri-axis Acc.	15 Young Volunteers	kNN, Feedforward Neural Network (FNN), SVM, Naïve Bayes (NB), Decision Tree (DT)	8 Human Activities	KNN 93.4%, FNN 90.7%,SVM 91.9%, NB 91.5%, DT 86%
Kwon, 2018[19]	Smartwatch	Two Volunteers	ANN, Random Forest (RF)	Eleven Activities	ANN 95%, RF 92.5%
Altun, 2010 [20]	Xsens Awinda Acc.	Eight Subjects	kNN, SVM,ANN, Least-Squares Method (LSM), Bayesian Decision Making (BDM)	19 Different Activities	kNN 98.2%, SVM 98.6%, ANN 86.9%, LSM 89.4%, BDM 99.1%

Video-based HAR



- Using video records or the sequence of images
- The Charades dataset (**Training Set**: 7985 videos, 157 activities, **Validation Set**: 1863, **Test Set**: 2000 videos)
- Smartphones Data Set (30 volunteers, Six activities : Walking, Walking upstairs, Walking downstairs, Sitting, Standing, Laying)

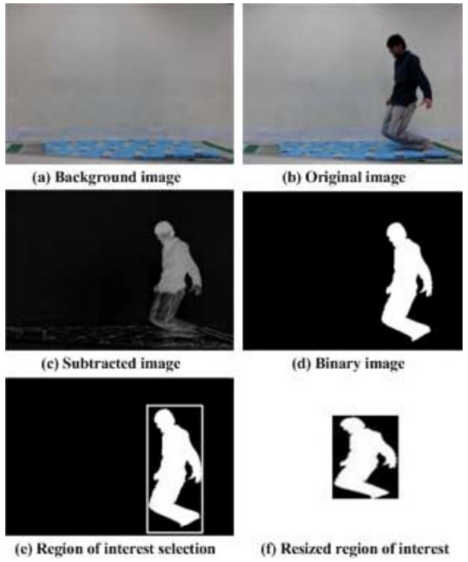
Frame 384 Frame 420 Frame 468 Frame 481 Frame 487



Abnormal Human Activity Recognition for Elderly Home Care

Khan et al. (2011)

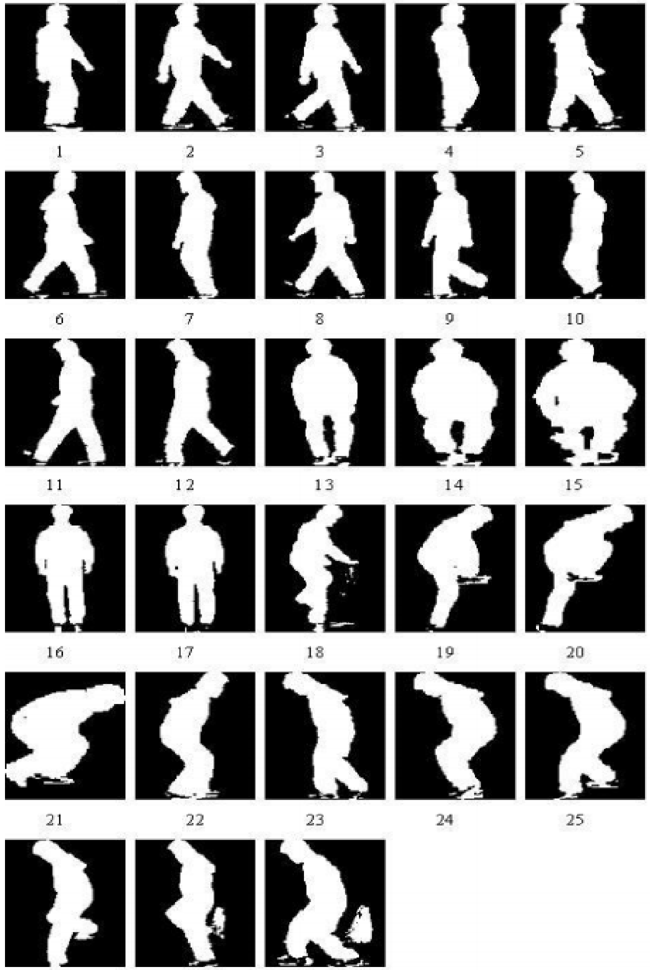
- Video sensor based (multiple cameras)
- six abnormal activities; forward fall, backward fall, chest pain, faint, vomit, and headache
- Six persons (4 men, 2 women) performed the activities by repeating ten sequences for each activity.
- k-means, Hidden Markov Model (HMM)
- Recognition rate of 95.8%



Chang et al. (2009)

Automatic nursing home systems

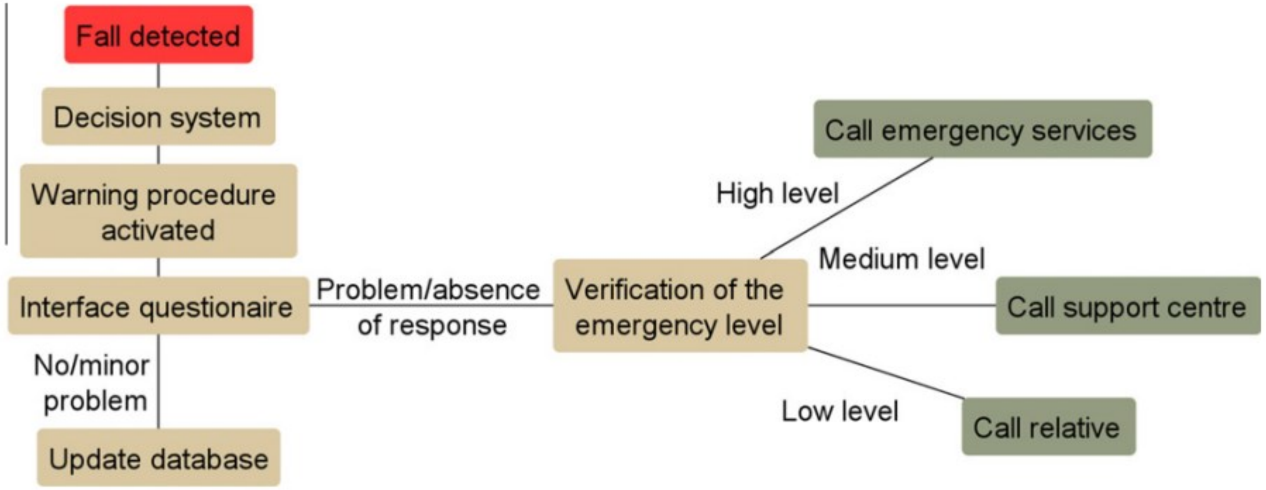
- Optoelectronics method
- Fuzzy rule approach
- There are six action datasets, which are done by six persons.
- Six actions: walking from left to right, walking from right to left, jumping, crouching, climbing up and climb down.
- Recognition accuracy of 91.8%



He et al. (2012)

Fall Detection

- Using Smartphone
- Smartphone in this system is worn on the waist.
- Five different patterns: vertical active, lying, sitting or static standing, horizontal active and fall.
- Support Vector Machine (SVM)



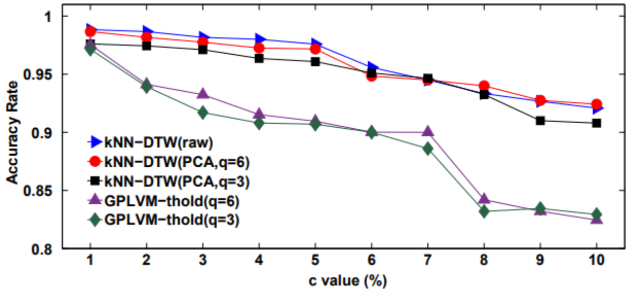
Alaqtash et al. (2011)

Classification of pathological gait

- The discrimination of gait patterns of healthy, cerebral palsy (CP) and multiple sclerosis subjects.
- GRFs
- Twelve healthy adults, four spastic diplegic cerebral palsy patients, four multiple sclerosis patients
- A total of 19 features
- Nearest neighbor classifier (NNC) and artificial neural networks (ANN)
- The classification accuracy is 95%

Classification of pathological gait

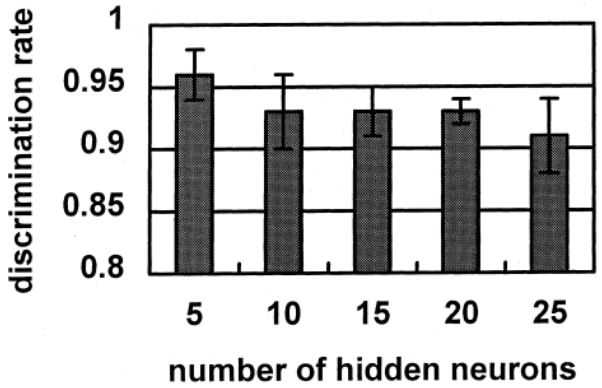
- Discriminate between healthy and pathological gait patterns as a result of stroke or acquired brain injury (ABI)
- Kinect skeletal tracking sequences, pressure mat
- 20 healthy young adults, 20 mobility impaired adults
- 30 steps for each walking condition
- Features: Joint angles, Velocity and acceleration, Upper limb, Trunk, Lower limb
- k-nearest neighbor, Gaussian Process Latent Variable Model



Dolatabadi et al. (2017)

Classification of pathological gait

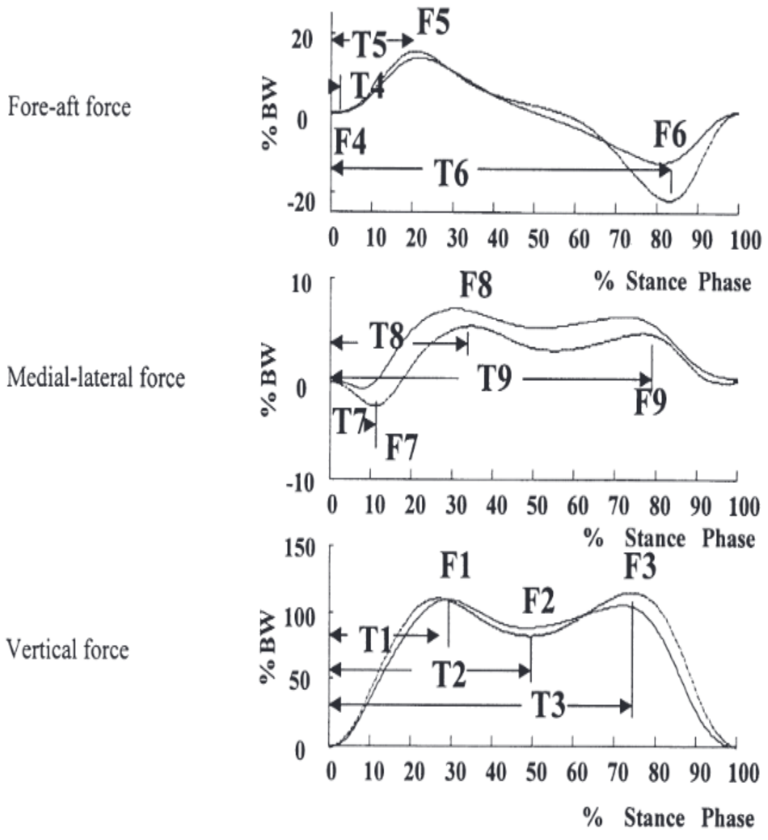
- The discrimination of gait patterns of healthy and ankle arthrodesis.
- Force platforms
- 40 control trials and 23 patient trials for training and 19 patient trials for validation. Ten normal subjects for comparison
- Time domain features
- Three-layered feed-forward back propagation neural network
- The classification accuracy is 95.8%



Wu and Su (2000)

Clinical implications of surgery or rehabilitation

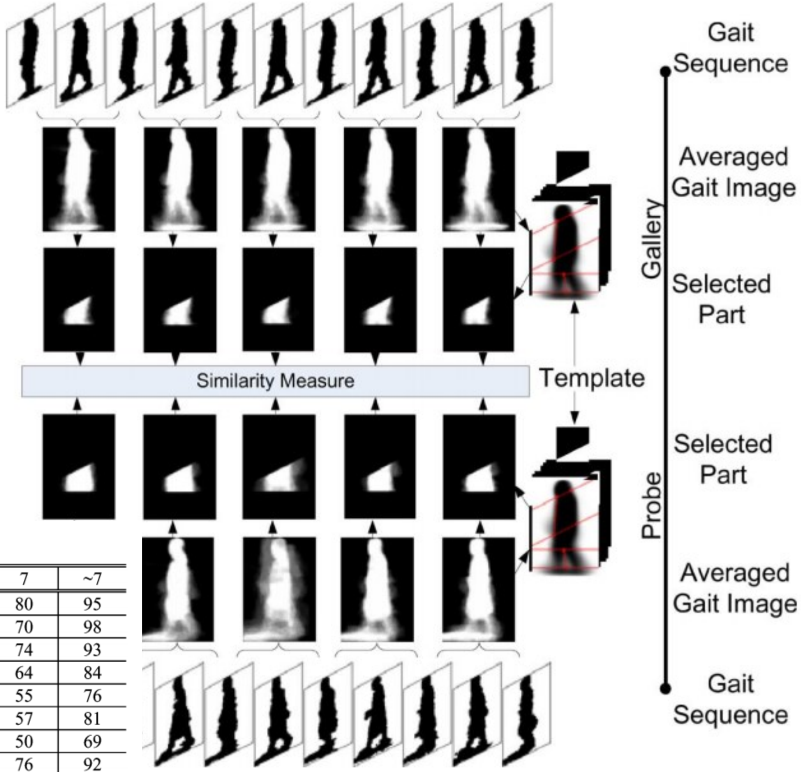
- To classify the gait patterns of patients with ankle arthrodesis and normal subjects
- Two force plates
- 10 healthy persons and 10 patients who had solid arthrodesis of the ankle
- A total of nine force parameters, stance phase period
- The genetic algorithm neural network (GANN), traditional artificial neural network(ANN)
- The classifications accuracies are 98.7% for GANN and 89.7% for ANN



Wu and Su (2000)

Person identification and gender classification

- Human gait is a promising biometrics resource.
- Silhouette-based gait analysis
- Head, arm, trunk, thigh, front-leg, back-leg, and feet.
- AGIs in the gallery set.
- SVM-based



EXPERIMENTAL RESULTS FOR HUMAN GENDER RECOGNITION FROM AVERAGED GAIT IMAGES

	0	1	~1	2	~2	3	~3	4	~4	5	~5	6	~6	7	~7
A	98	85	98	86	96	89	93	85	98	73	98	74	98	80	95
B	98	91	100	83	98	91	94	80	98	74	98	76	98	70	98
C	96	93	96	72	96	87	91	80	96	76	94	76	96	74	93
D	82	71	86	71	84	78	86	68	82	69	80	73	85	64	84
E	84	76	74	64	79	78	79	64	83	67	81	66	81	55	76
F	76	80	83	71	78	81	76	73	73	65	75	66	76	57	81
G	74	74	81	64	78	81	74	76	72	67	78	57	71	50	69
H	92	84	92	76	91	81	89	70	88	70	89	68	88	76	92
I	84	88	93	76	81	81	84	71	88	66	84	66	86	69	86
J	93	88	92	85	92	86	87	59	94	71	90	64	94	76	86
K	94	88	91	82	97	85	97	76	97	73	91	76	97	67	94
L	82	82	76	76	82	82	82	82	67	79	73	70	76	48	79

The first column contains the IDs for the 12 probes and the other columns contain the recognition rates for different parts. Column "0" lists the averaged gait images. "1," "2," "3," "4," "5," "6," and "7" indicate that gender is recognized by head, arm, trunk, thigh, front-leg, back-leg, and feet, respectively. "~1," "~2," "~3," "~4," "~5," "~6," and "~7" indicate that gender is recognized by the averaged gait image without head, arm, trunk, thigh, front-leg, back-leg, and feet, respectively. The table entries are percentages.

Li et al. (2008)

Person identification and gender classification

1. Detection and extraction of the moving human body
2. Extraction of human gait signature by the joint angles and body points
3. Motion analysis and feature extraction for classifying gender in the gait patterns

- The SOTON database, DV cameras
- SVM classifier, 19 important features (joint angles, temporal and spatial parameters)
- The classification accuracy is 96% for 100 subjects

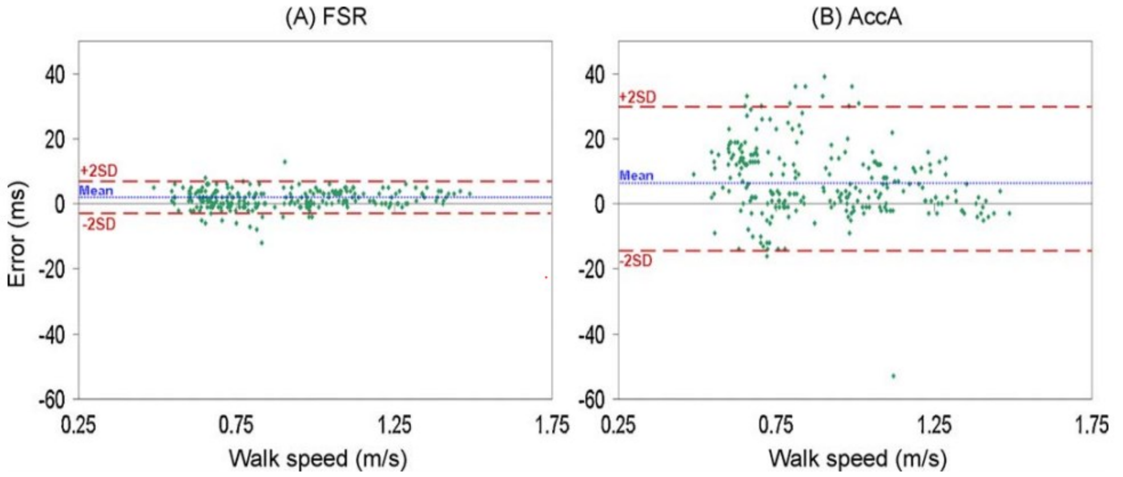
(a) Sample Image (b) Background Subtraction (c) Object Detection

Yoo et al. (2005)

Gait Event Detection

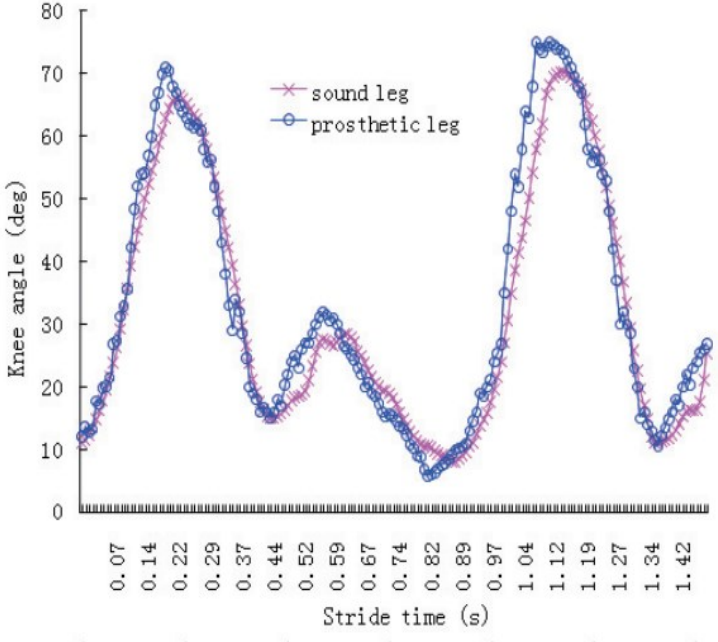
Hanlon et al. (2009)

- Twelve healthy individuals (eight males and four females)
- Three conditions: normal, slow, and altered (reduced knee ROM) walking
- Force sensing resistor (FSR), A force plate, A 6- camera Hawk motion analysis system, accelerometers
- The optimal accelerometer algorithm (AccA) was used.
- Mann–Whitney U-tests at a 95% confidence level



Analysis of gait pattern of the prosthetic limb

- Intelligent leg prosthesis
- According to the moving feature of human leg, and consists of the position, velocity
- Single-axis mechanism, Servo motors
- Non-linear dynamics model and Proportional-Derivative (PD) control algorithm to improve the robustness, speed of response, intelligent behavior and position accuracy of this servo system.
- Designed by CAD software
- The lower limb gait data of healthy young woman is gathered from VICON MX motion capture system.



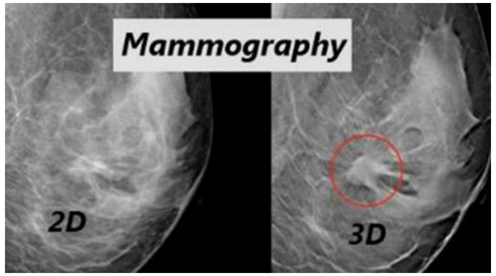
Zhang, et al. (2010)

Processing Radiological Images as 3D and Applications of Biomedical Engineering

Overview

Radiological Images	3D Printer	Finite Element Method
3D Reconstruction	3D Printer Technologies	3D Modeling
File Format and Software	3D Printer Software	Application Methods and Software

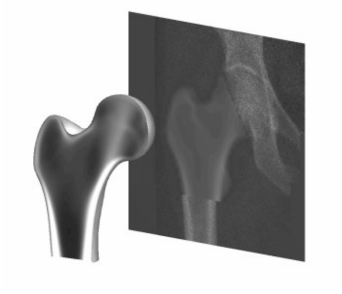
Radiological Images



Mammography

Convertible as 3-Dimensional Model	Produces 2-Dimensional Images	Produces 3-Dimensional Images but can not be converted as 3D
• Computed Tomography (CT) • Magnetic Resonance (MR) • Dental Panoramic Digital X Ray • Digital Subtraction Angiography (DSA) • Positron Emission Tomography (PET-CT) • Single Photon Emission Computed Tomography (SPECT)	• Digital X-ray - Conventional X-ray • C-arm X-ray • Digital Fluoroscopy	• Digital Mammography • Ultrasonography • Color Doppler Ultrasonography • Bone Densitometer (DEXA)

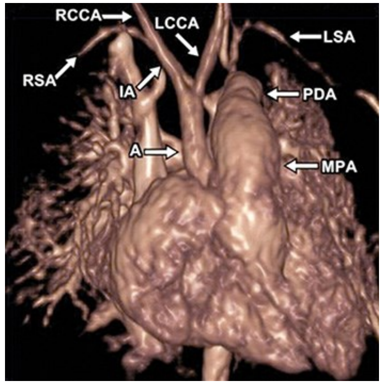
Ultrasound



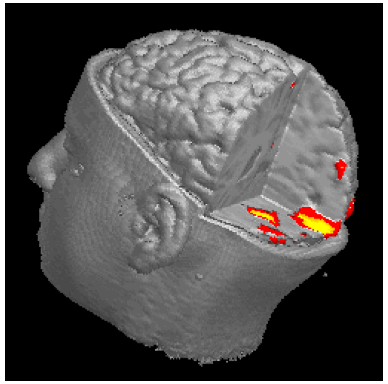
DEXA

3D Image Reconstruction

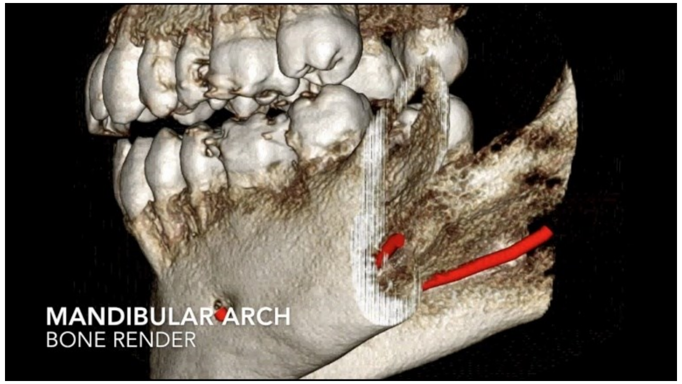
CT



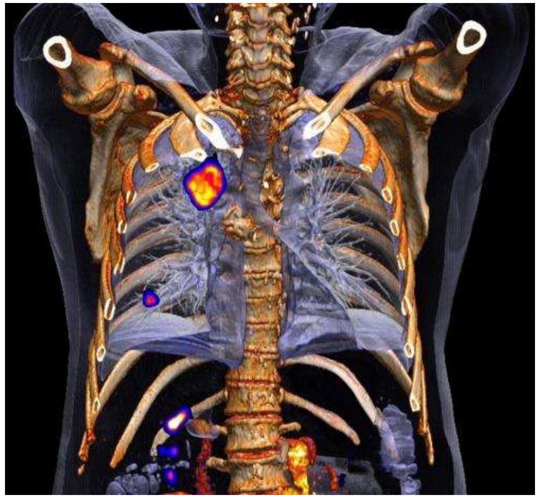
DSA



MR



Dental Panoramic X-Ray



PET-CT

SPECT

Digital Imaging and Communications in Medicine (DICOM)

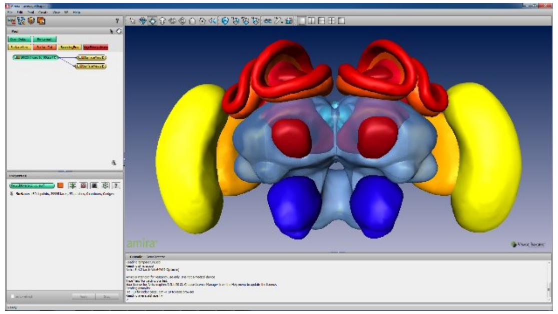
- DICOM® is the **international standard** to transmit, store, retrieve, print, process, and display **medical imaging** information.
- All radiological devices support this format.
- DICOM Format Contents
  - The imaging modalities properties (Device, Voltage, Current,…)
  - Patient Information (Name, Gender, Age, Birth date)
  - Image Properties (Slice thickness, pixel spacing,…)
  - Study Information (Date, ID,…)
  - Clinical Information (Protocol Name, Coord. Center,…)

Calculating 3D from 2D

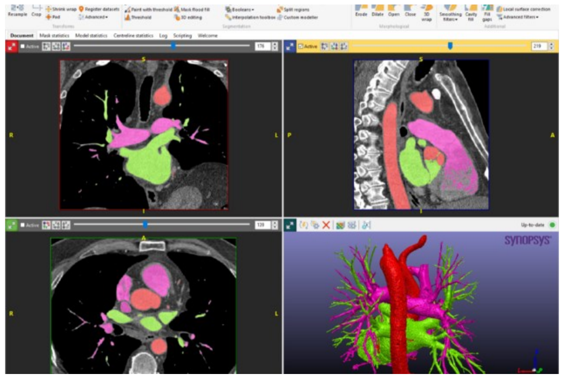
- Import DICOM image to software
- Image Segmentation
  - Threshold algorithm
  - Region-Growing algorithm
  - Morphological segmentation
  - Neural network segmentation
  - Adaptive segmentation
  - Semi-Automatically segmentation
- Calculating 3D model from Mask
- Editing and repairing
- Export STL files for 3D printer (STEP, IGES, Parasolid or STL files for FEA)

3D Reconstruction Software

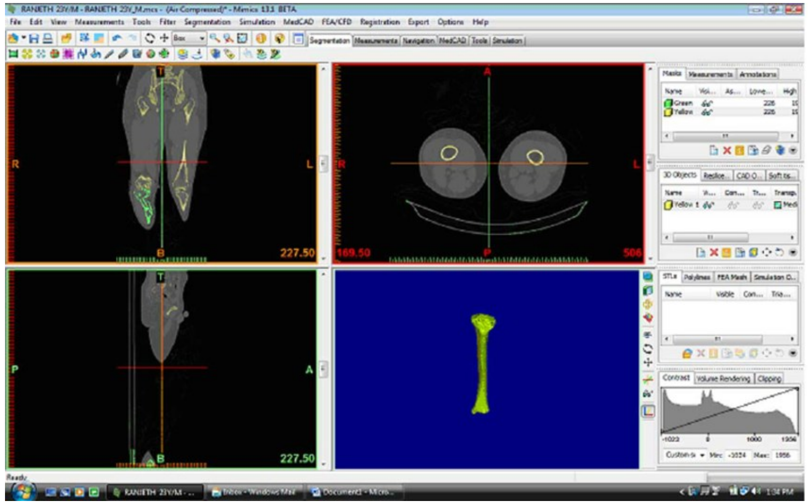
Free	Commercial
3DSlicer	OsiriX
ITK-SNAP	MIMICS
MeVisLab	Amira
MIPAV	Simpleware
MITK	Analyze



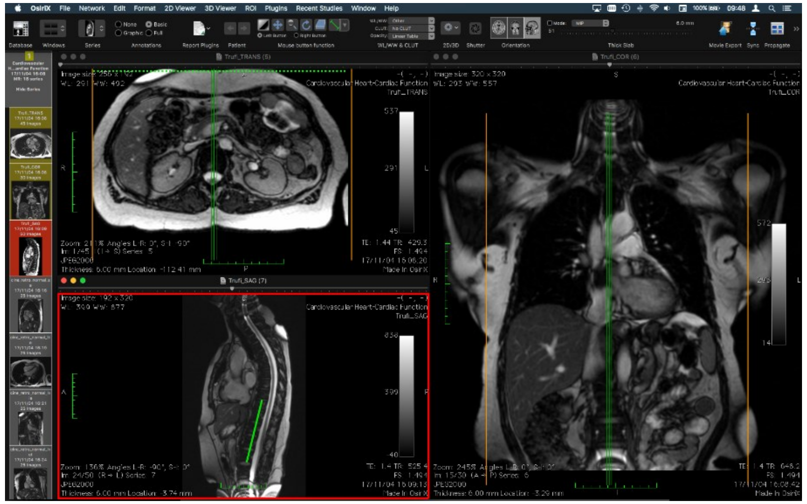
Amira



Simpleware



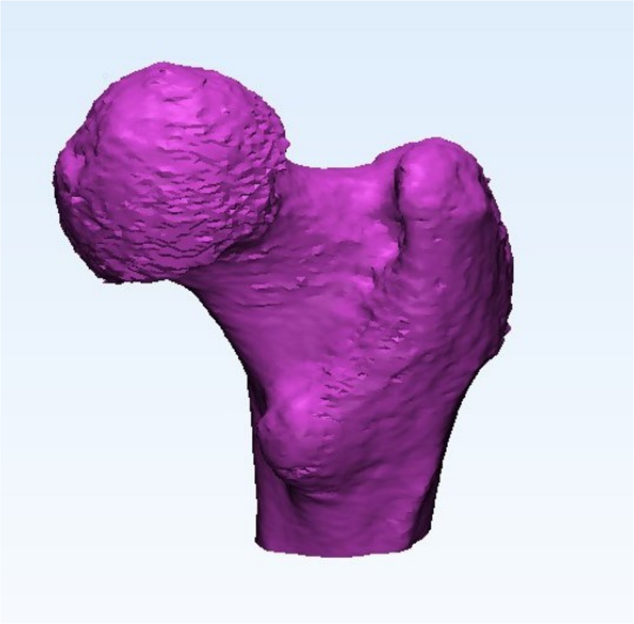
MIMICS



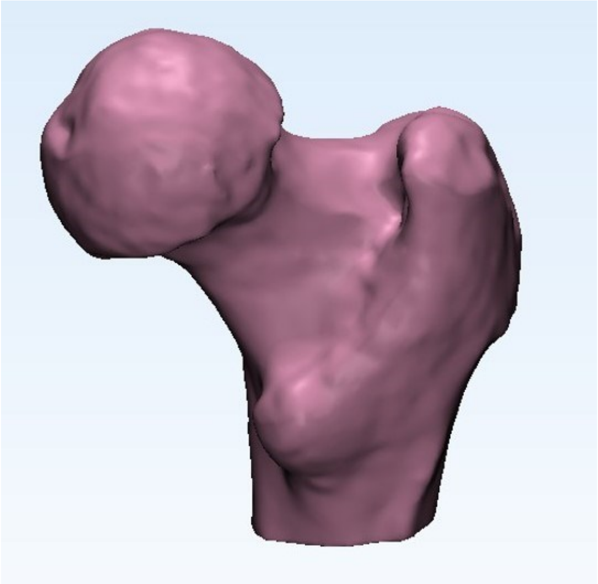
OsiriX

Editing and repairing

- Rough surfaces can cause problems both in 3D printer and analysis software. Therefore, they should be cleaned using various operators.



Before editing the femoral head



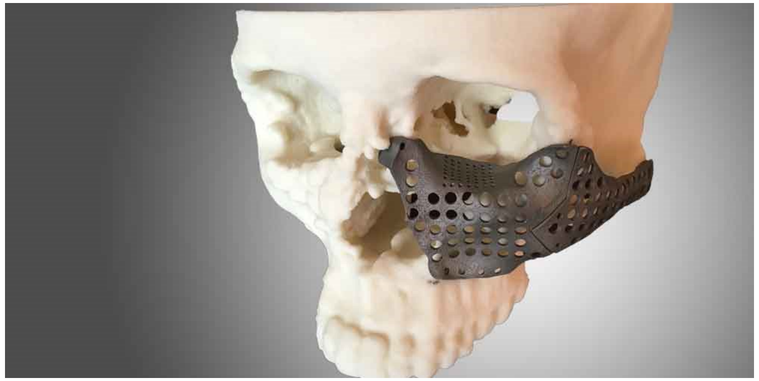
After using Wrap and smooth operators

- Wrap operator provides that gaps are closed.
- The smooth operator removes rough surfaces in the 3D model.

3D Printer Technologies

3D printers can use many different technologies. The differences between the technologies are related to how the layers are created.

Some technologies used by 3D printers;

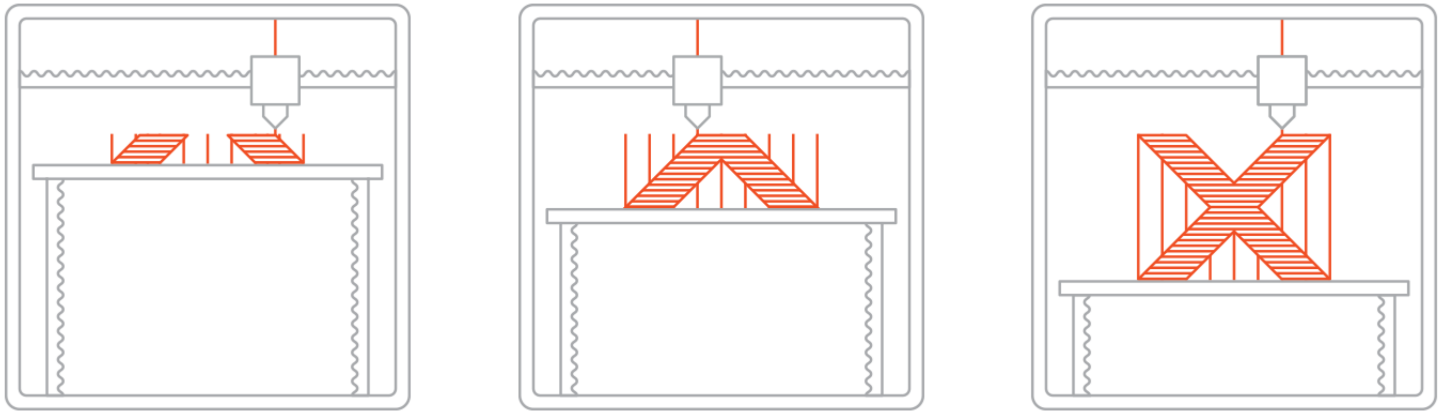


- SLS (Selective Laser Sintering)
- FDM (Fused Deposition Modeling)
- STL-SLA (Stereolithograhpy)

These technologies are some of the most used 3d technologies.

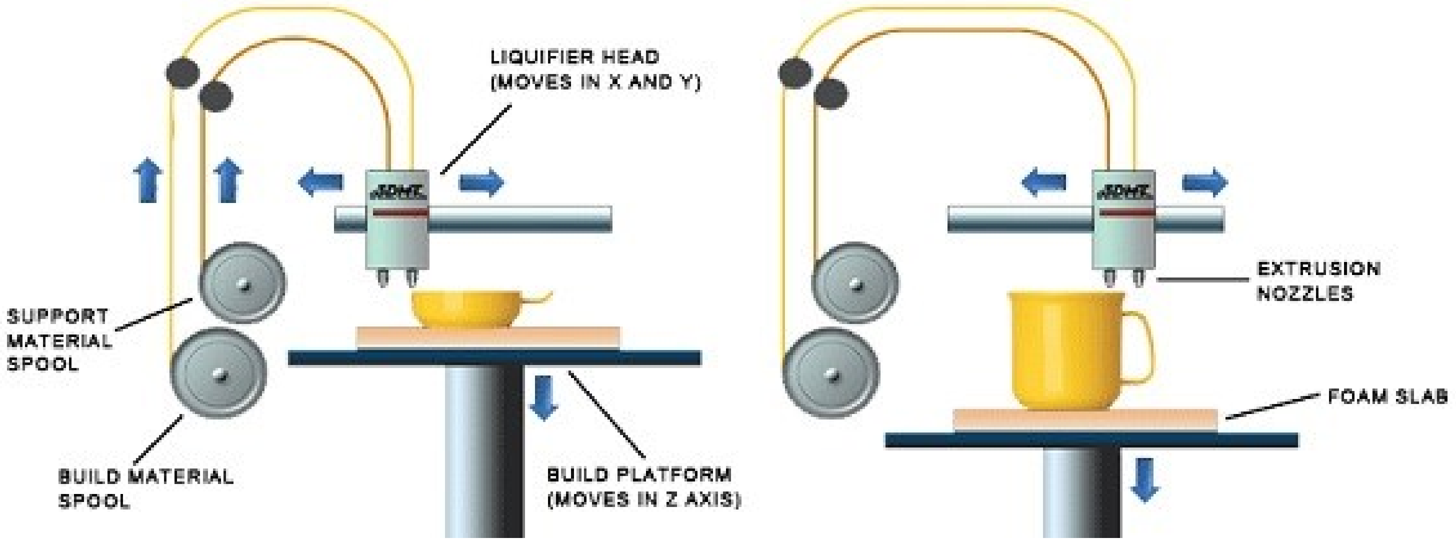
FDM | Fused Deposition Modeling

- FDM is a filament-based technology where a temperature-controlled head extrudes a thermoplastic material layer by layer onto a build platform. A support structure is created where needed and built in a water-soluble material.



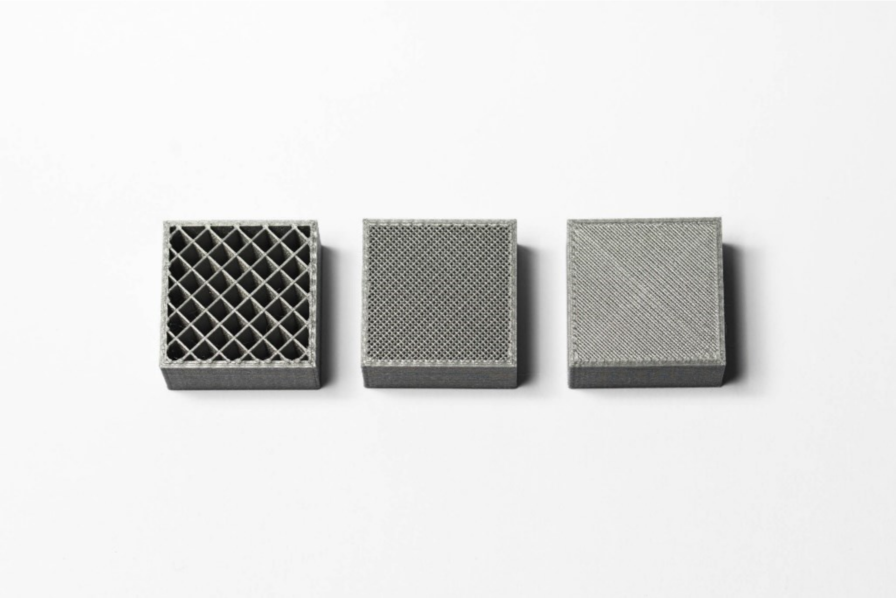
Why choose FDM?

- The great advantage of FDM is the durable materials it uses, the stability of their mechanical properties over time, and the quality of the parts. The production-grade thermoplastic materials used in FDM are suitable for detailed functional prototypes, durable manufacturing tools and low-volume manufacturing parts.



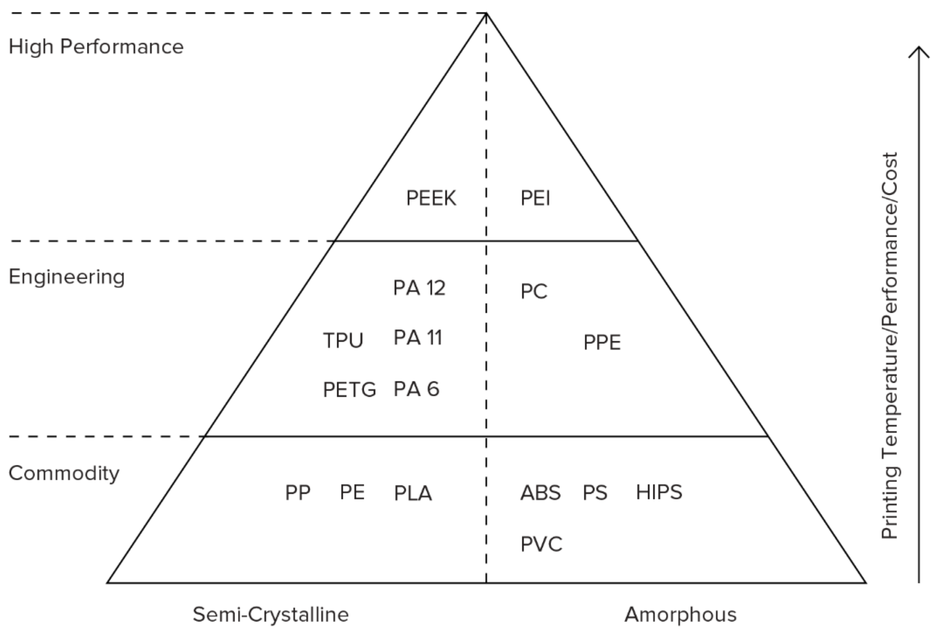
Infill & Shell Thickness

- FDM parts are usually not printed solid to reduce the print time and save material. Instead, the outer perimeter is traced using several passes, called the shell, and the interior is filled with an internal, low-density structure, called the infill.



Materials for FDM

- ABS (Acrylonitrile Butadiene Styrene)
- ABSi (Acrylonitrile Butadiene Styrene – Biocompatible)
- ABS-M30i (Acrylonitrile Butadiene Styrene – Biocompatible)
- PLA (Polylactic acid)
- PC (Polycarbonate)
- PET (PolyEthylene Terephthalate)
- Thermoplastic elastomer (TPE)

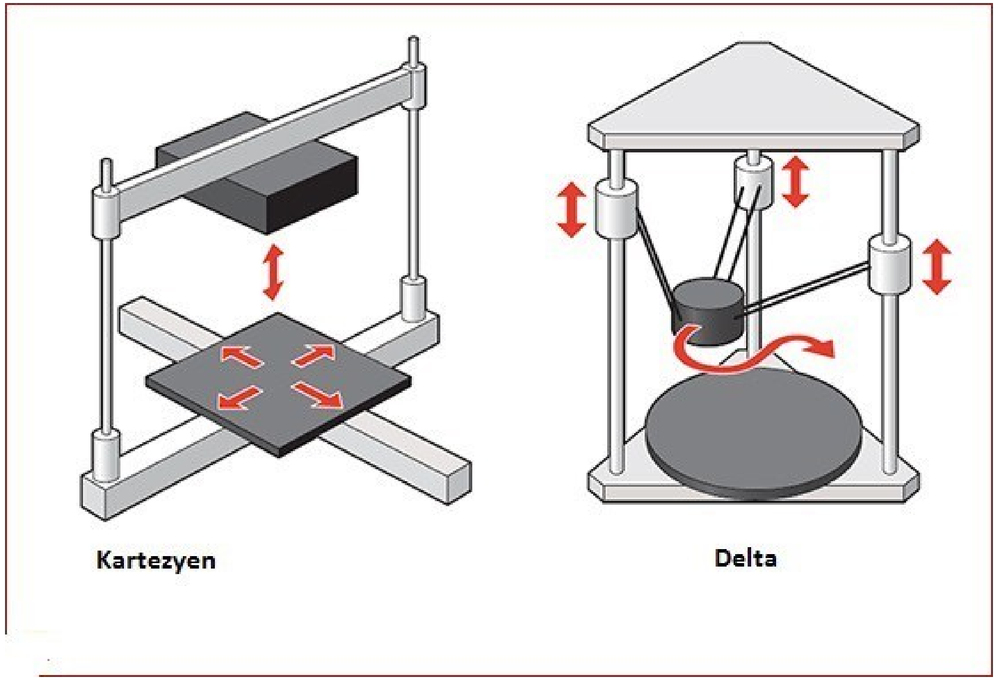


Material	Characteristics
ABS	•Good strength •Good temperature resistance •More susceptible to warping
PLA	•Excellent visual quality •Easy to print with •Low impact strength
Nylon (PA)	•High strength •Excellent wear and chemical resistance •Low humidity resistance

*https://www.3dhubs.com/knowledge-base/fdm-3d-printing-materials-compared

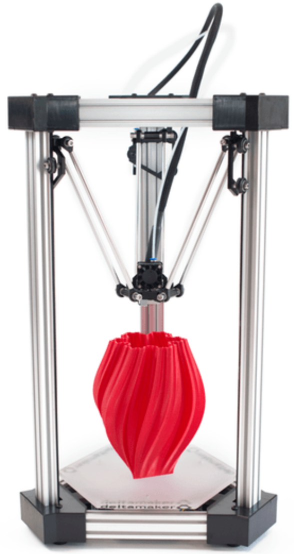
Cartesian, Delta, and Polar

- **Cartesian:** These printers are named after the most widely used coordinate system which helps robots to decide where and how to move. They will typically have a square print bed which will run along the Y-axis. The X-axis will carry the print head and for the Z-axis (up and down) movement



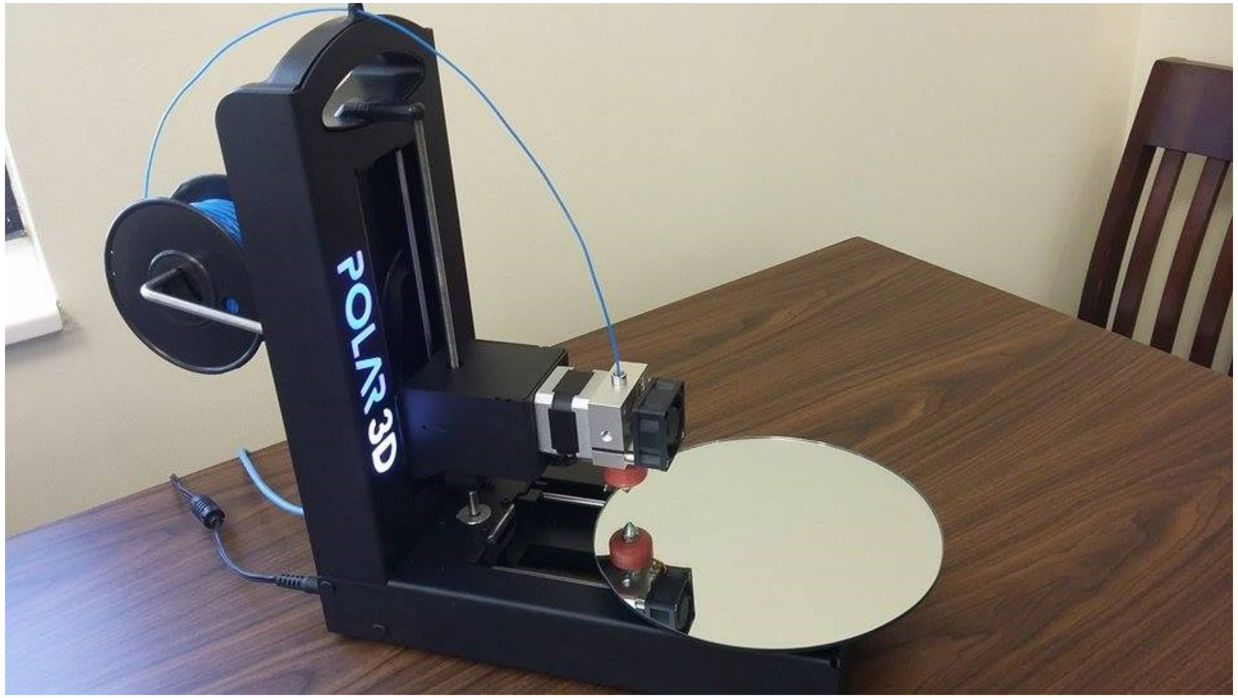
Cartesian, Delta, and Polar

- **Delta:** Deltas will usually feature a circular print bed. The extruder will be suspended above that by three arms in a triangular configuration (thus the name “Delta”). These nifty robots were designed for speed and they also have the advantage of a print bed that does not move which could be advantageous for certain prints.



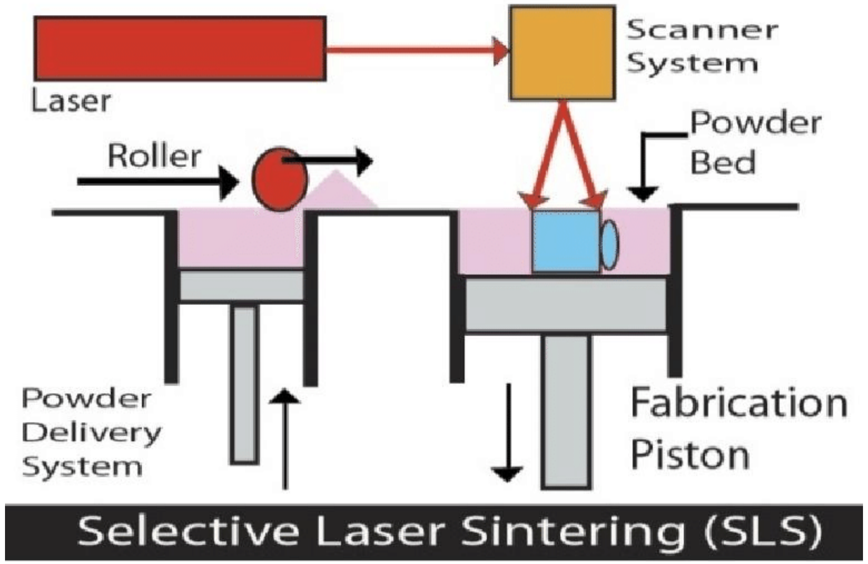
Cartesian, Delta, and Polar

- **Polar:** These machines use polar coordinates. This system is similar to the Cartesian except that the coordinate sets describe points on a circular grid rather than a square.



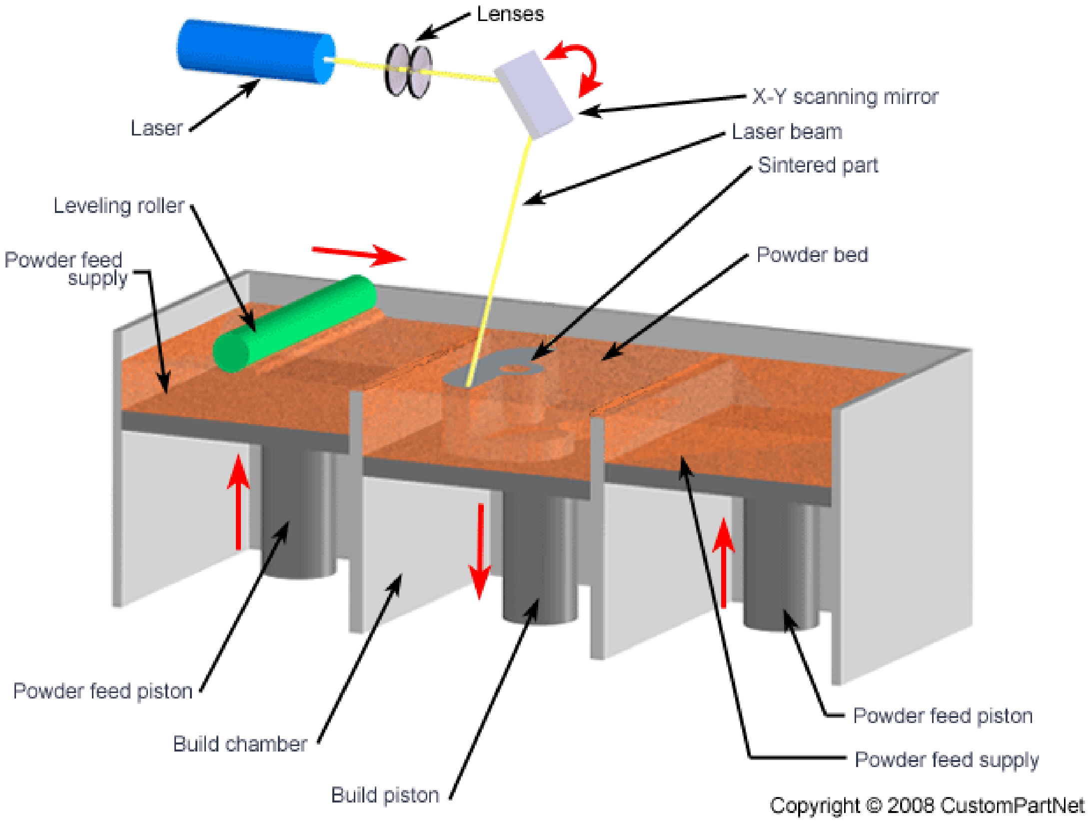
SLS | Selective Laser Sintering

- SLS uses a high-powered $C0_2$ laser to fuse small particles of powdered material to create 3 dimensional parts. The laser selectively fuses powdered material by scanning X&Y cross-sections on the surface of a powder bed. The model is built one layer at a time from supplied 3D CAD data. SLS is capable of producing highly durable parts for real-world testing.



SLS | Selective Laser Sintering

- During SLS, tiny particles of plastic, ceramic or glass are fused together by heat from a high-power laser to form a solid, three-dimensional object.

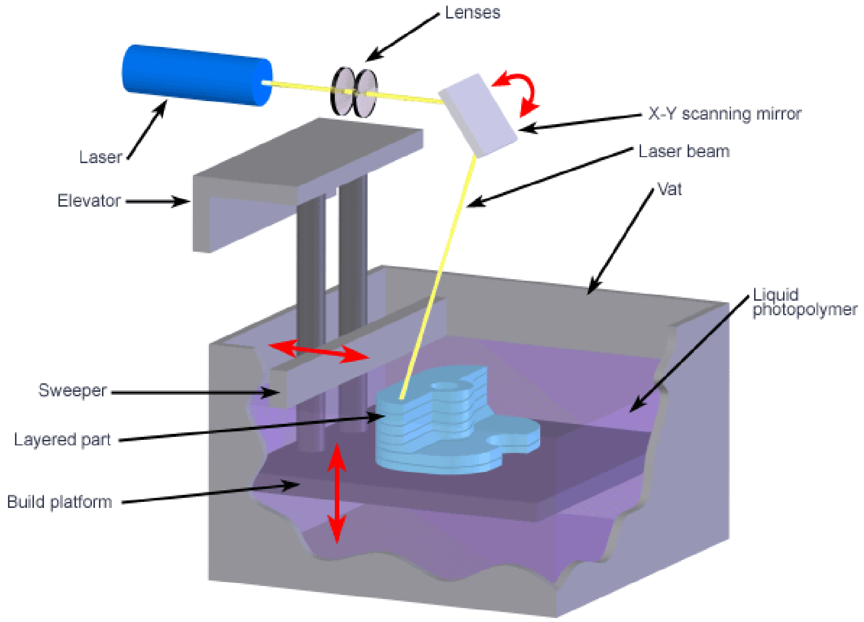


Advantages

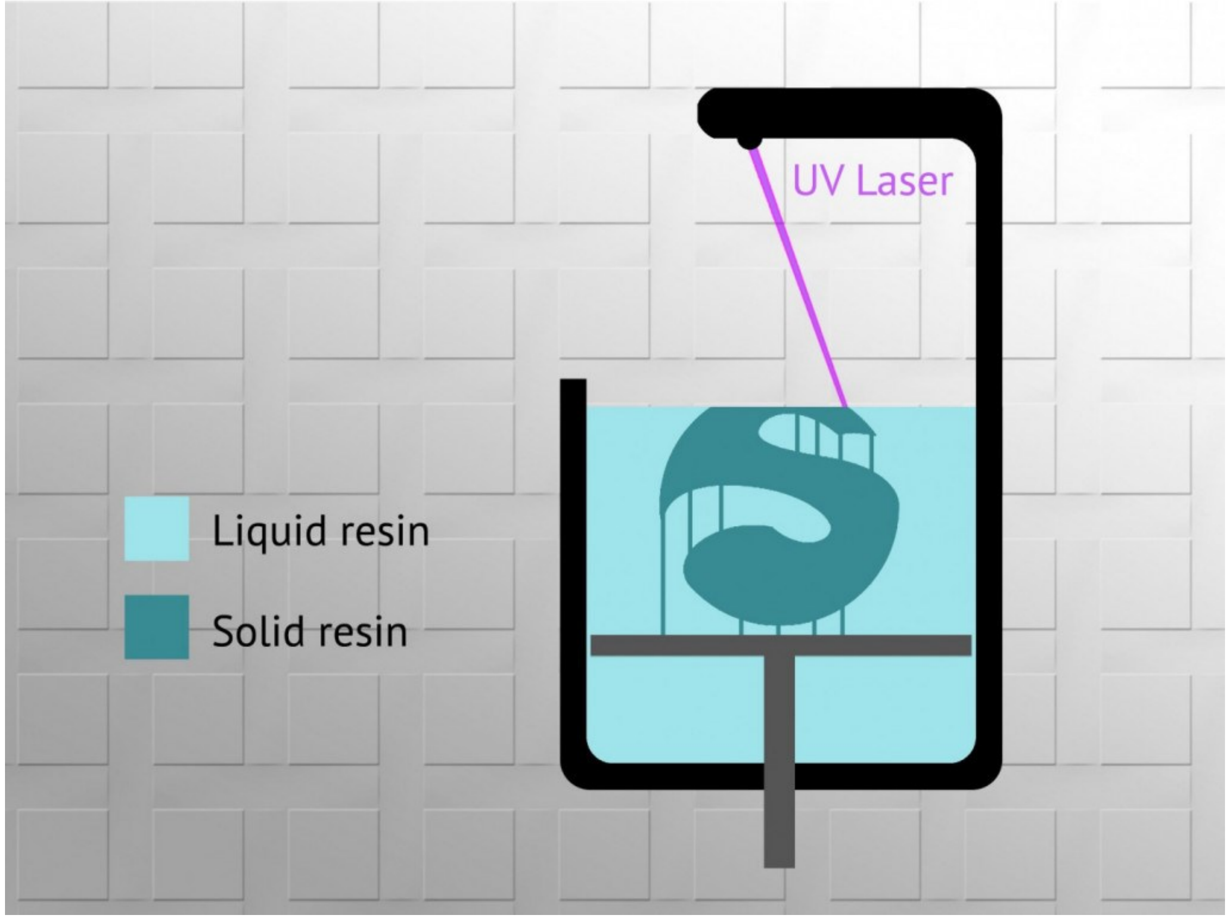
- Produce highly complex geometries
- Durable, high-heat and chemically resistant applications
- Impact-resistant parts for rigorous use
- Ideal for snap fits and living hinges
- Low-volume production solutions
- Major time and cost benefits
- Large build platforms available

SLA | Stereolithography

- Stereolithography is a laser-based technology that uses a UV-sensitive liquid resin. A UV laser beam scans the surface of the resin and selectively hardens the material corresponding to a cross section of the product, building the 3D part from the bottom to the top. The required supports for overhangs and cavities are automatically generated, and later manually removed.



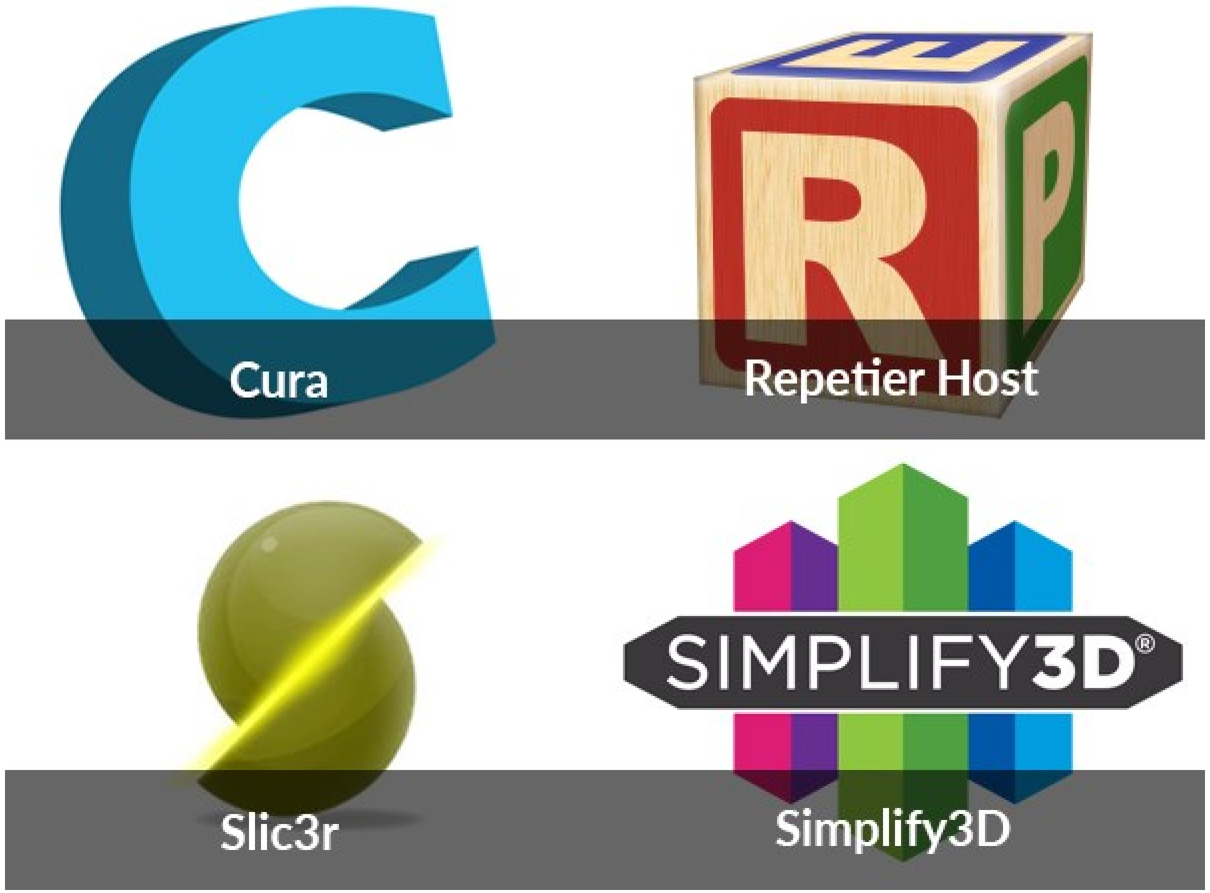
SLA | Stereolithography



Formlabs

https://www.youtube.com/watch?v=b-sIcYo8isI

3D PRINTER SOFTWARE

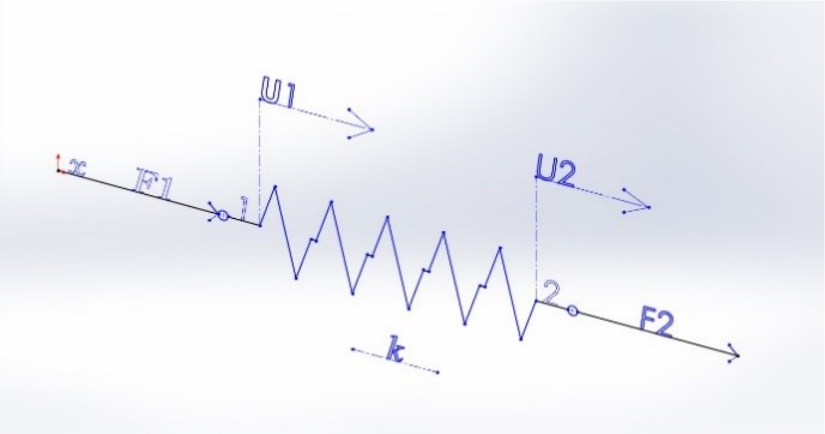


Some of the most used

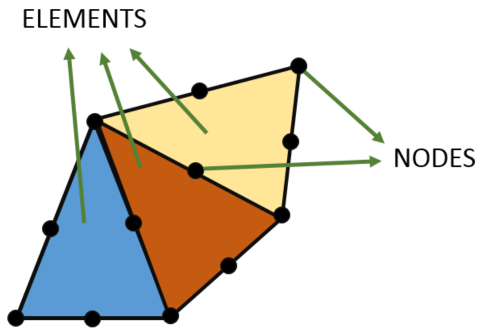
Others

Finite Element Method

- FEA is a numerical method designed to solve engineers' problems.
- Complex geometric shapes are divided into smaller pieces to define a limited number of elements.
- It was first used for stress analysis of aircraft bodies in 1956.
- When the forces f_1 and f_2 are applied, the displacements u_1 and u_2 occur.



Force and displacement on the spring.

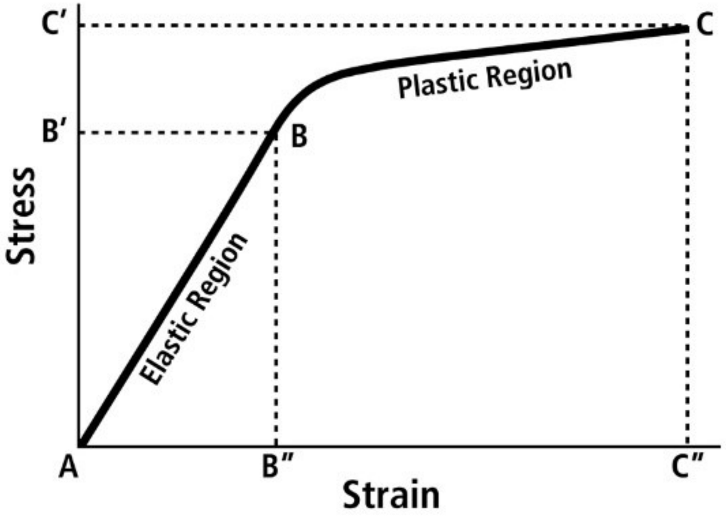


Elements and Nodes.

Finite Element Method

$$\begin{bmatrix} k & -k \\ -k & k \end{bmatrix} \begin{Bmatrix} u_1 \\ u_2 \end{Bmatrix} = \begin{Bmatrix} f_1 \\ f_2 \end{Bmatrix}$$

- k_e is the stiffness matrix for a spring element, u is the nodal displacement, and f is the nodal force.



Stress and strain relationship.

$$\varepsilon = \frac{\Delta u}{u_0}$$

ε is strain

$$\sigma = \frac{F}{A}$$

σ is stress ($\frac{N}{m^2}$),
F is force applied,

$$\sigma = E\varepsilon$$

E is Young's modulus

von Mises criterion states

$$\sigma_v{}^2 \geq \frac{1}{2}[(\sigma_1 - \sigma_2)^2 + (\sigma_1 - \sigma_3)^2 + (\sigma_2 - \sigma_3)^2]$$

σ_1, σ_2, σ_3 are principal stresses

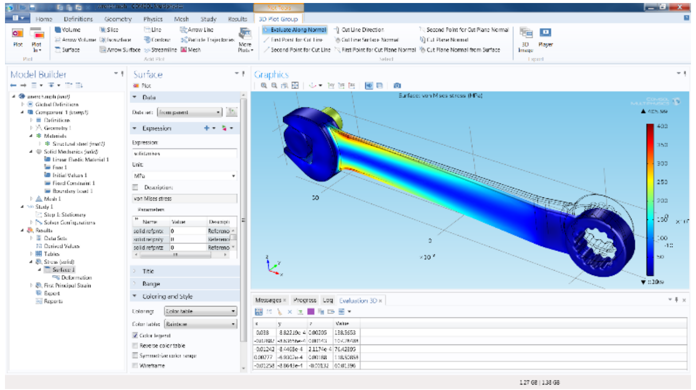
Finite Element Analysis (FEA)

Steps to solve the finite element problem;

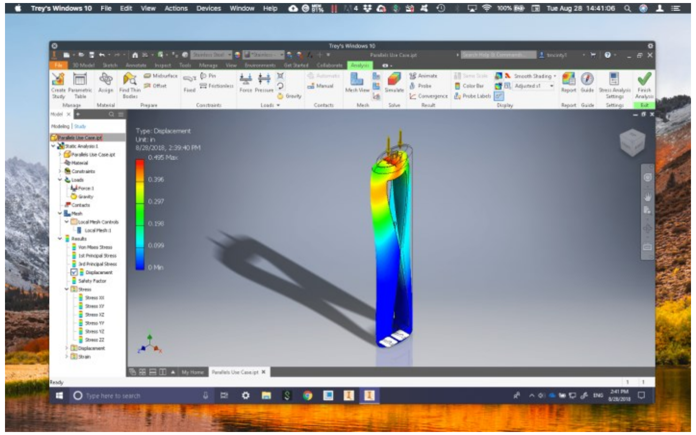
1. Import Geometry (STL, STEP, IGES, Parasolid, etc.)
2. Define Material Properties
3. Set Mesh Parameters
4. Define Boundary Condition
5. Apply Force and define force direction
6. Solve FE problem

Finite Element Software

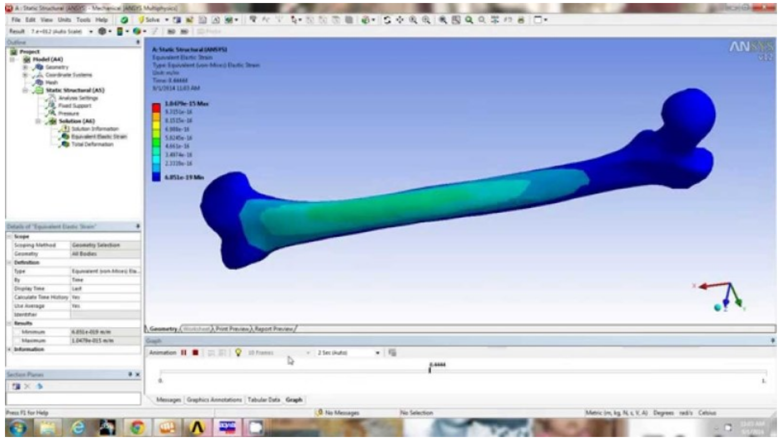
Free	Commercial
Elmer FEM solver	Ansys
FEBio	Abaqus
FEATool Multiphysics	Comsol Multiphysics
Hermes	ADINA
MFEM	Nastran
Range Software	Autodesk Simulation



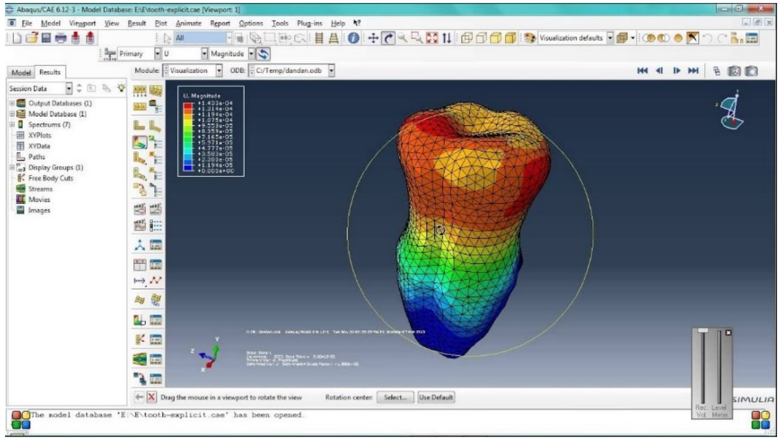
Comsol Multiphysics



Autodesk Simulation



Ansys



Abaqus

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Thanks for listening