

Characterizing shapes and motions

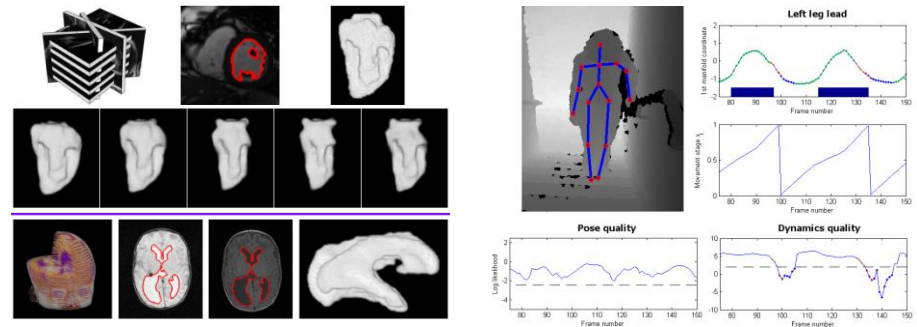
How can computer vision and deep learning help with astronomy image analysis?

Large scale visual data analysis

Computer vision, machine learning and deep learning

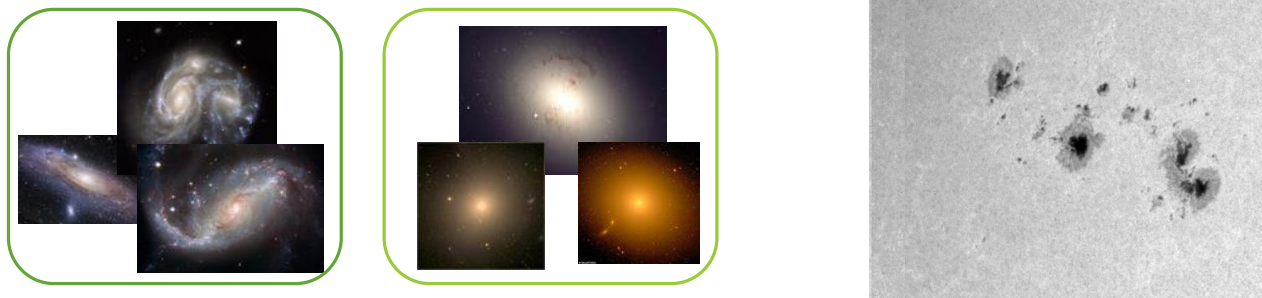
Healthcare applications

- Medical image analysis
- Looking at people and their activities
- Diagnosis & assistive technologies



Astrophysics applications

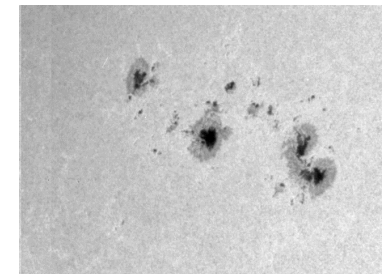
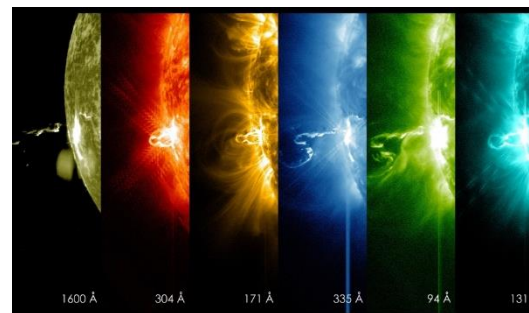
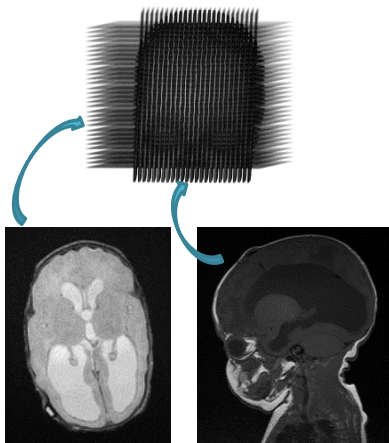
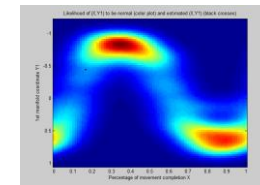
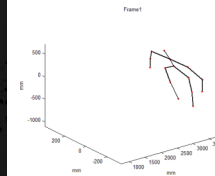
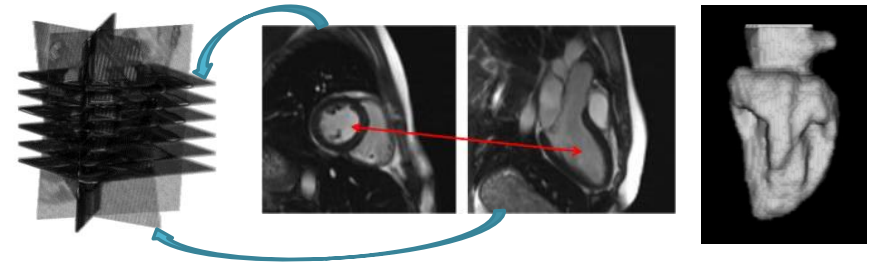
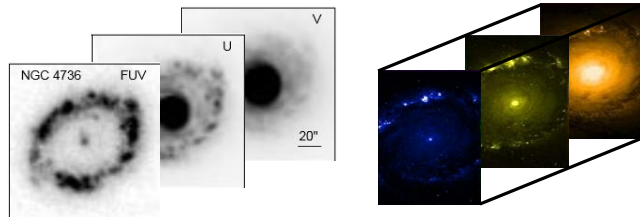
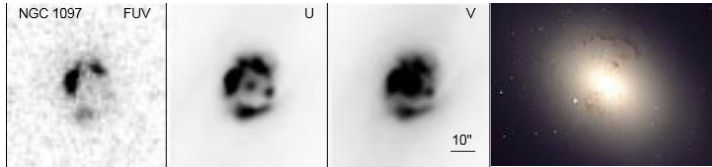
- Catalogue generation from grand surveys
- Detection, monitoring, and prediction of transient events and dynamic objects



Similar tasks

Characterising
shapes

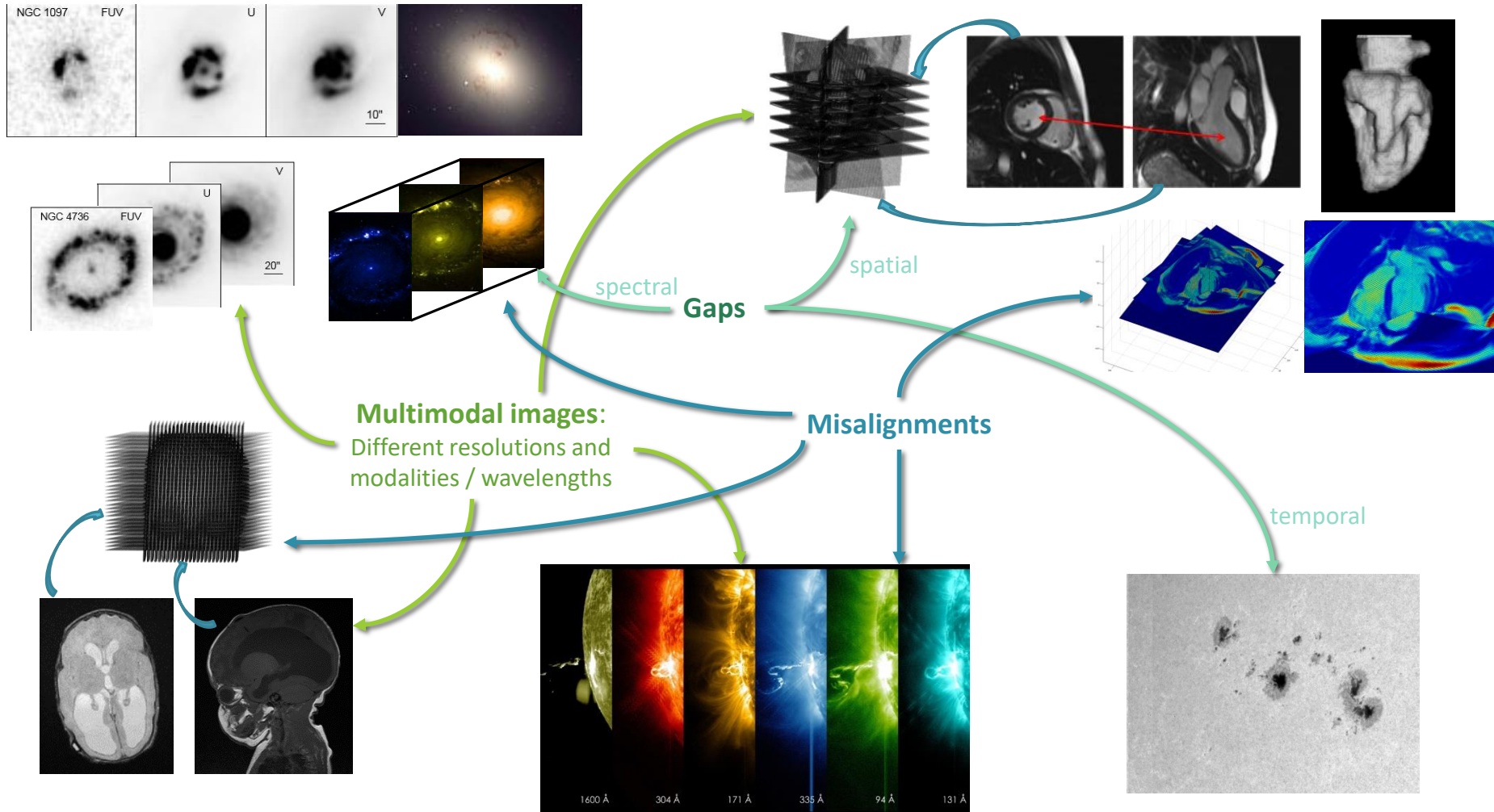
Characterising
motions



Similar challenges

Big data

Interpretability

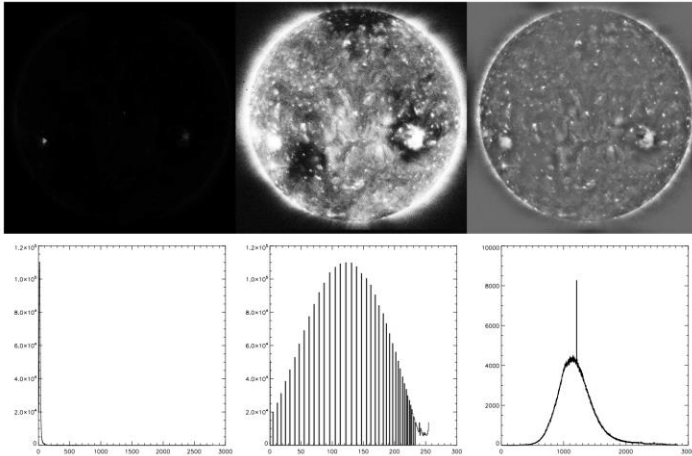


Scientific image properties



Scientific vs natural images

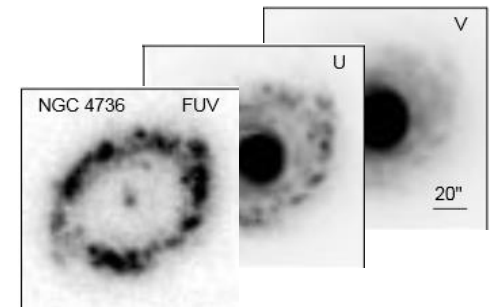
- High dynamic ranges, low contrasts



- Noise



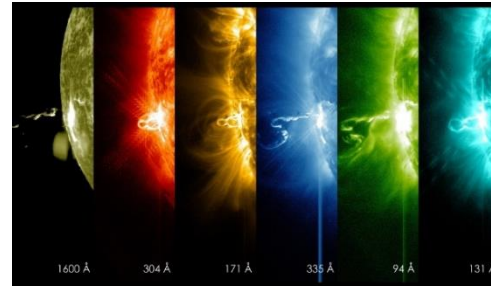
- Meaning of the intensity value



- Need specifically designed algorithms

Some more challenges

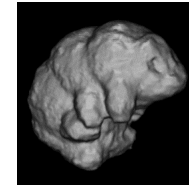
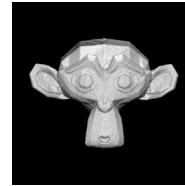
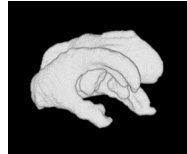
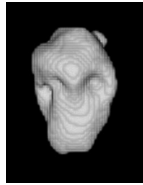
- Lack of ground-truth → semi-supervised learning, transfer learning
- *Can we transfer learnt models?*



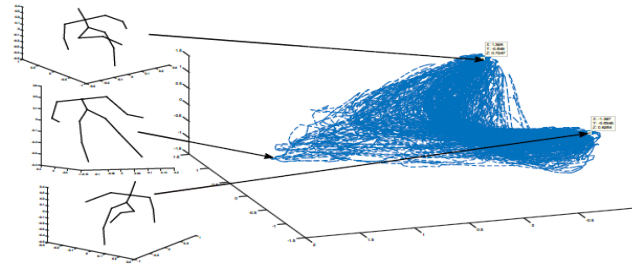
- *Meaning* of the systems and results?
 - Integrating **knowledge**
 - **Explaining** models and results

Overview: Characterising shapes and motions

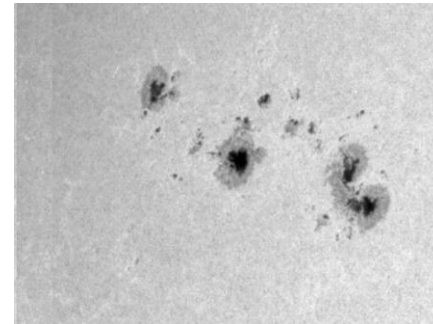
Shape reconstruction



Shape analysis

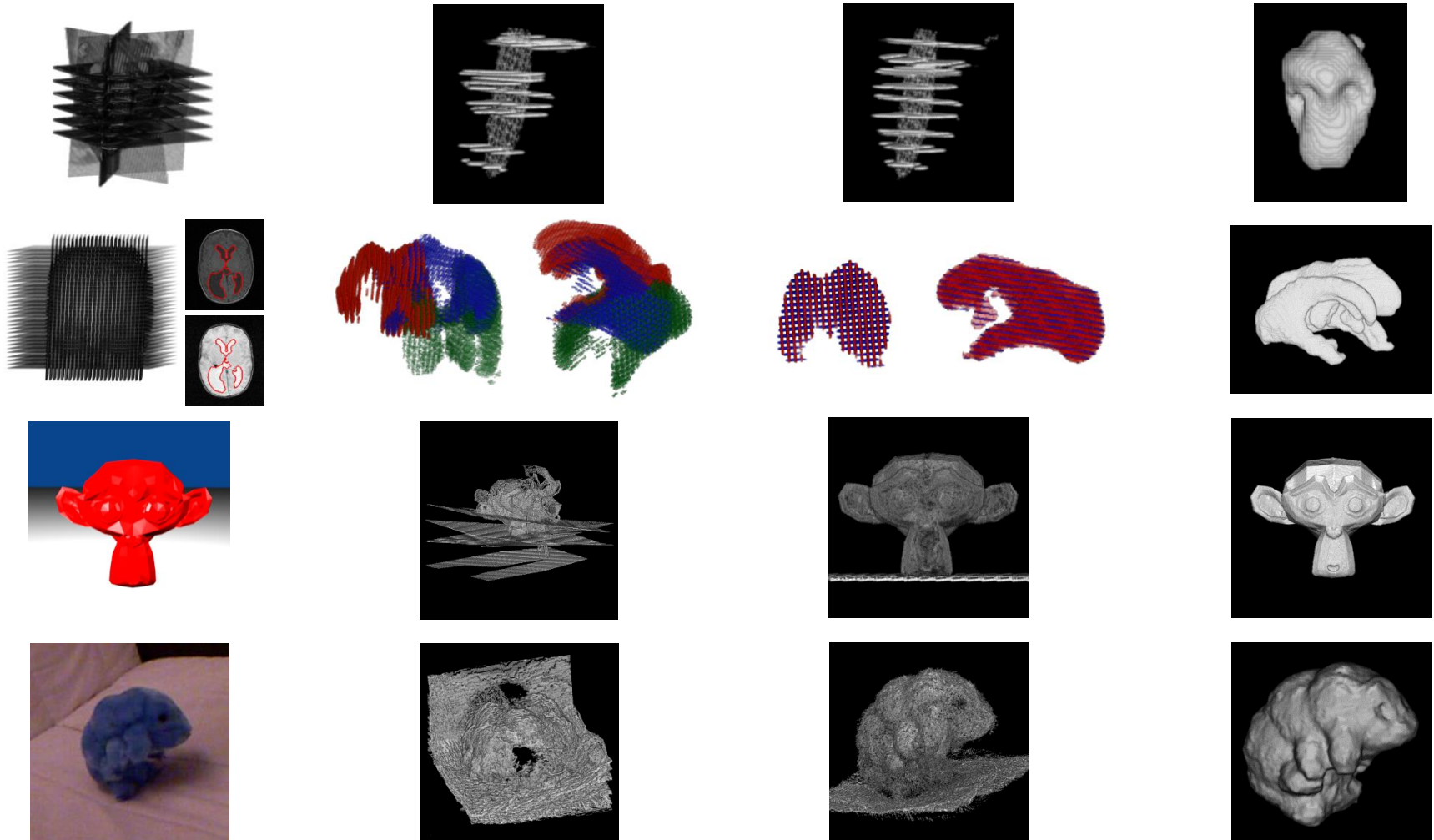


Motion analysis



IReSISD: shape modelling for multimodal data

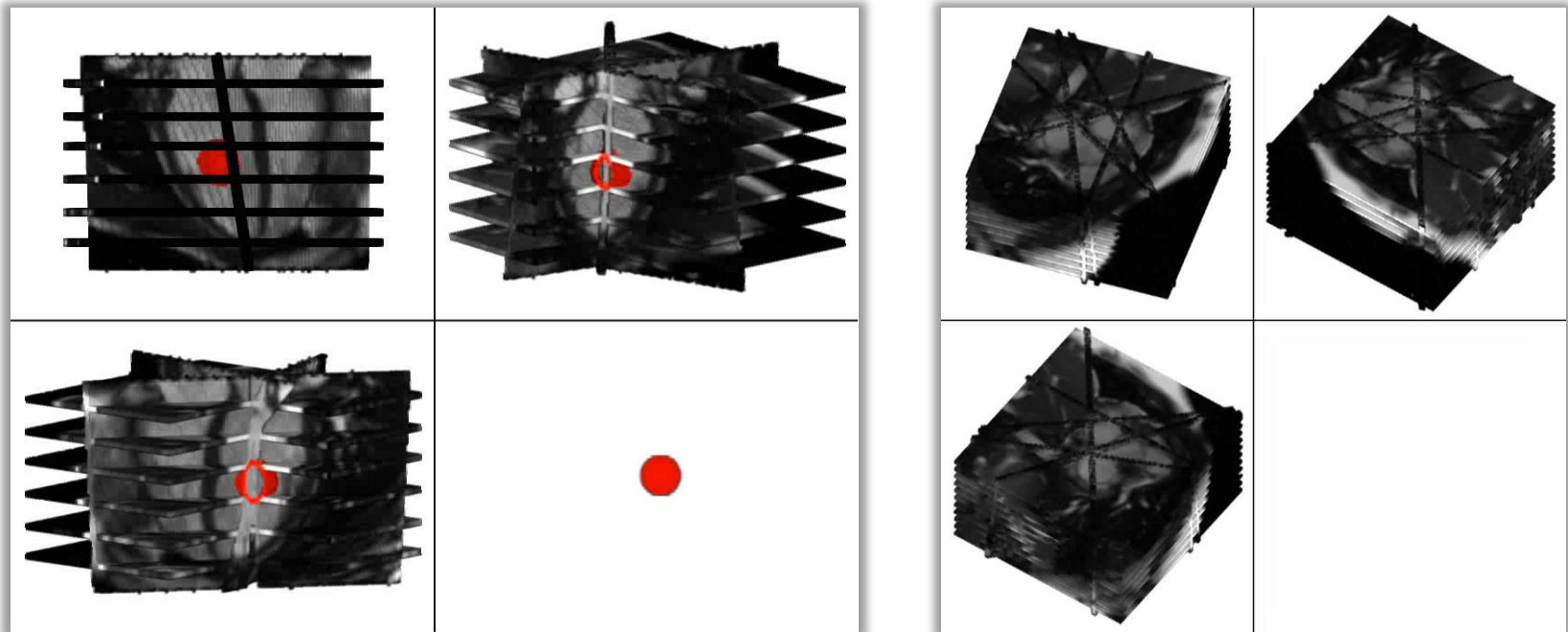
Modelling from multimodal data with heterogeneous resolutions, misalignments, and gaps



- [1] Adeline Paiement, Majid Mirmehdi, Xianghua Xie, Mark Hamilton: **Registration and Modeling from Spaced and Misaligned Image Volumes**. *IEEE Transactions on Image Processing*, Vol. 25, Issue 9, 2016
- [2] Adeline Paiement, Majid Mirmehdi, Xianghua Xie, Mark Hamilton: **Integrated Segmentation and Interpolation of Sparse Data**. *IEEE Transactions on Image Processing*, Vol. 23, Issue 1, 2014
- [3] Adeline Paiement, Majid Mirmehdi, Xianghua Xie, Mark Hamilton: **Simultaneous Level Set interpolation and segmentation of short- and long-axis MRI**. *MIUA*, pp. 267-272, 2010

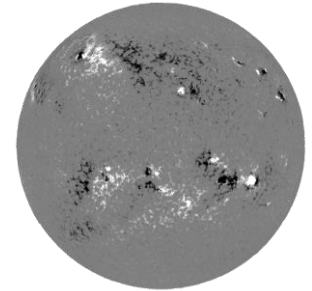
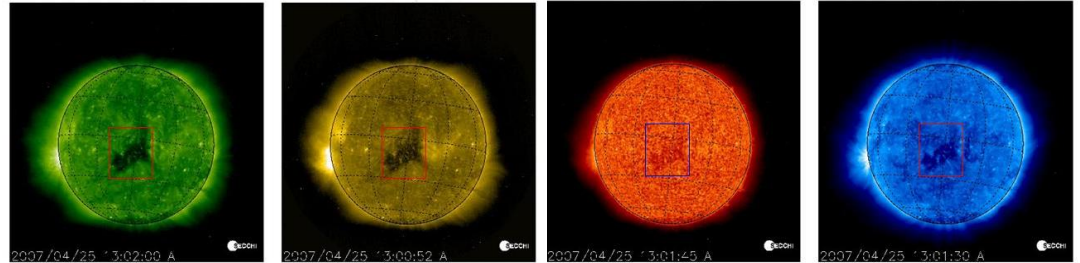
IReSISD: shape modelling for multimodal data

Modelling from multimodal data with heterogeneous resolutions, misalignments, and gaps



Some examples of application in astronomy

- Reconstruction of solar active regions from multispectral images



Goals:

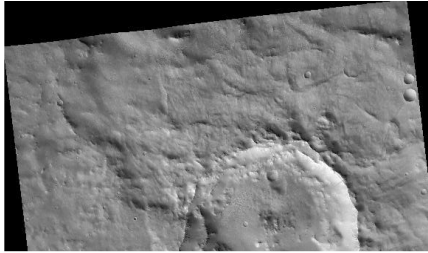
- 3D/4D reconstruction of active regions
- Studying the mechanisms of solar activity
- Prediction of solar activity

Collaboration with Jean Aboudarham, Paris-Meudon Observatory

Some examples of application in astronomy

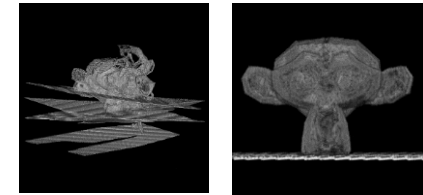
- Modelling of the Martian terrain from orbital multispectral images

1. 3D point cloud: stereoscopic photometry

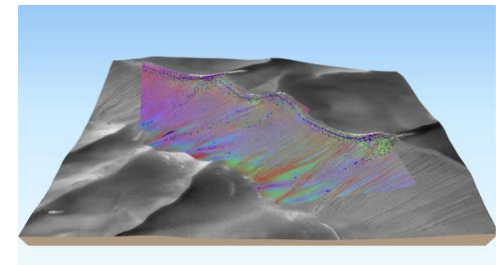


Stereoscopic photometry – [Wikipedia]

2. Fusion of point clouds and modelling by IReSISD



3. Deep learning-based segmentation of terrain types and unmixing of compositions



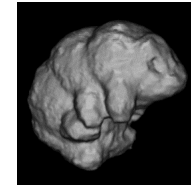
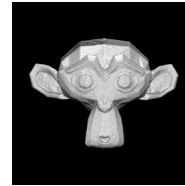
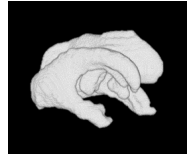
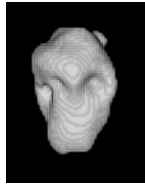
Goal:

- Identification of typical and abnormal geological properties

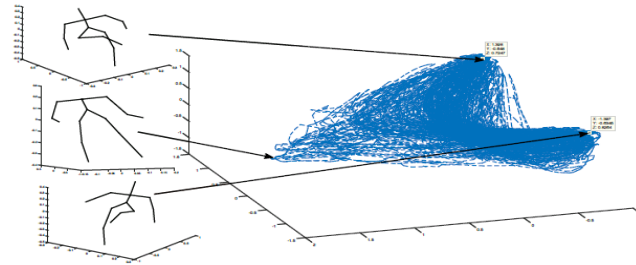
Collaboration with Sylvain Douté, Institut de Planétologie et d'Astrophysique de Grenoble

Overview: Characterising shapes and motions

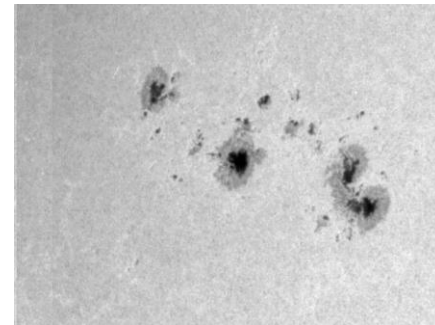
Shape reconstruction



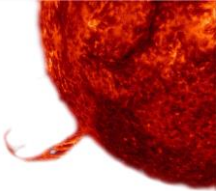
Shape analysis



Motion analysis



Characterising shapes: solar radio bursts

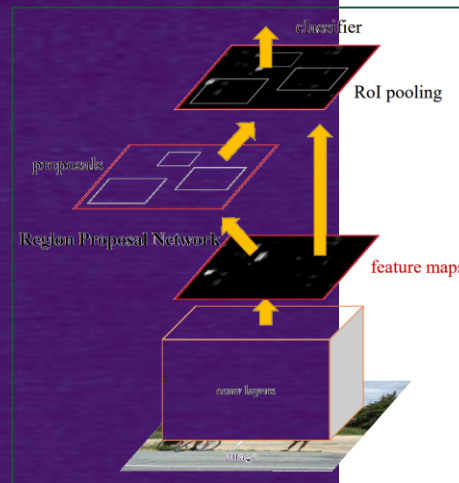
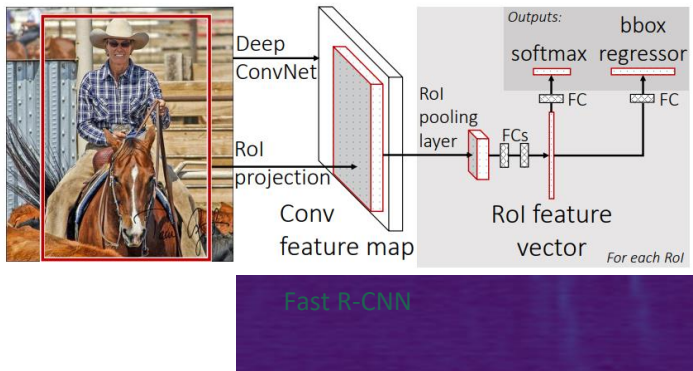
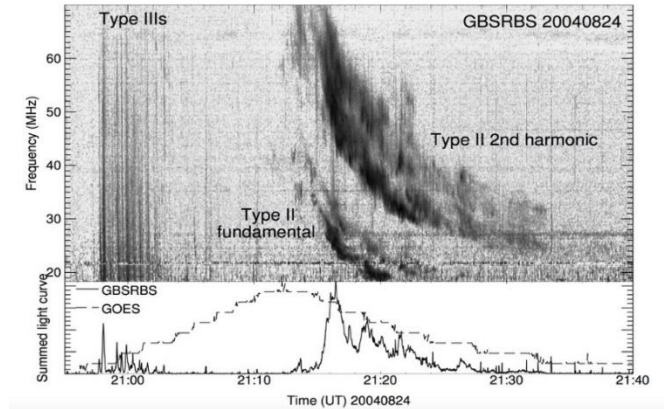


Joint solving of interdependent tasks

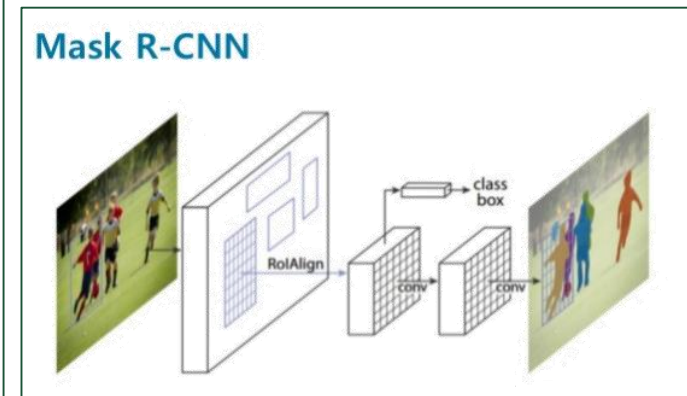
- **Detection**
- **Classification** (types II and III)
- **Regression** of properties (duration, decrease rate, harmonic)

using deep learning

- **Multi-task**

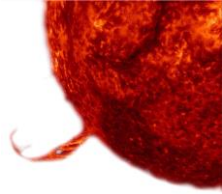


Faster R-CNN



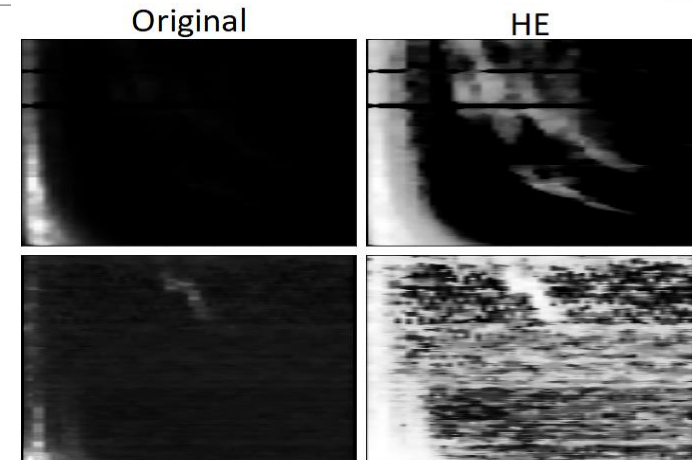
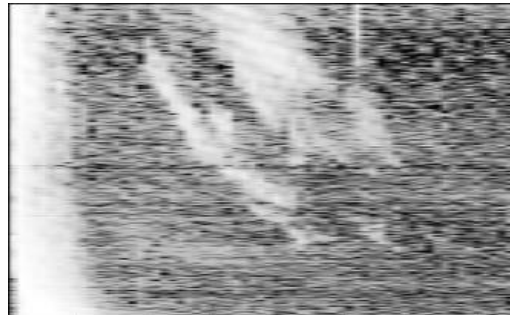
Collaboration with Jean Aboudarham, Paris-Meudon Observatory

Adapting deep learning models to spectrograms

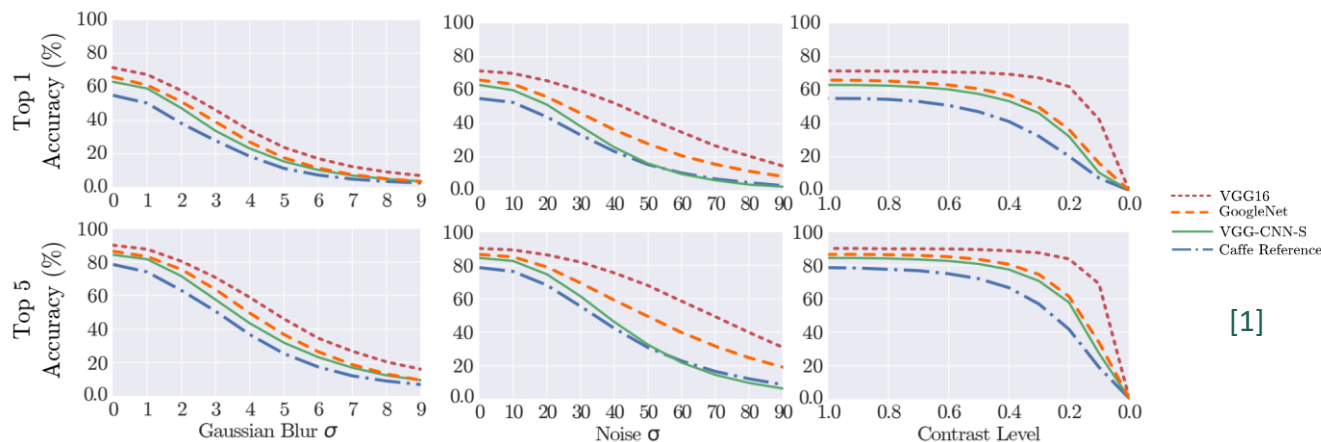


Challenges to transfer learning:

- Noise
- High dynamic range
- Low contrast



Classification results suffer from low image quality



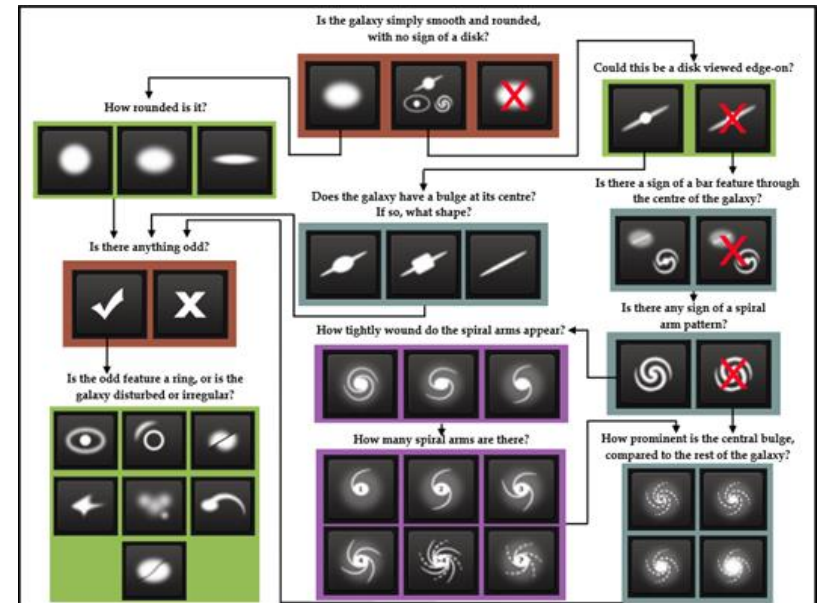
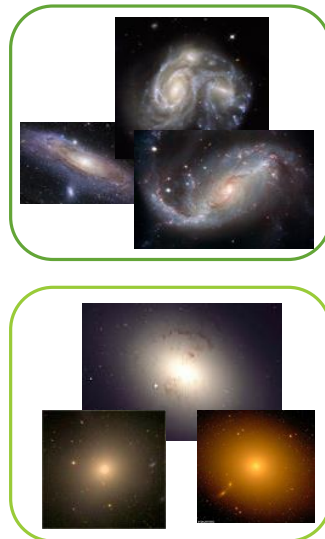
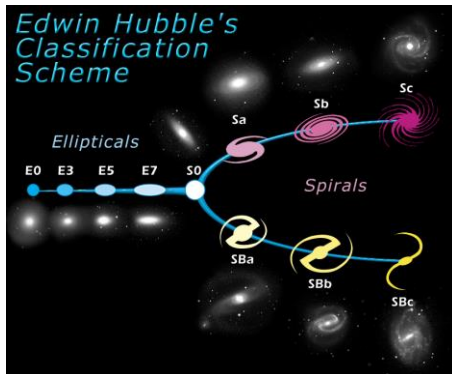
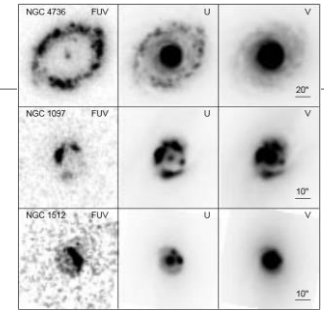
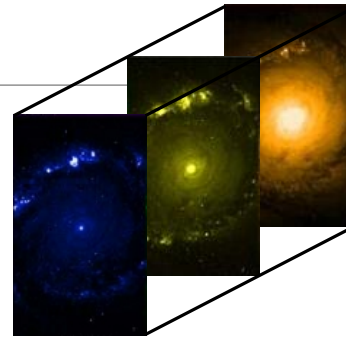
[1]

➤ Image enhancement? Adaptive transfer learning?

Galaxy morphology

Joint solving of interdependent tasks:

- Classification of morphology types
- Regression of morphology parameters



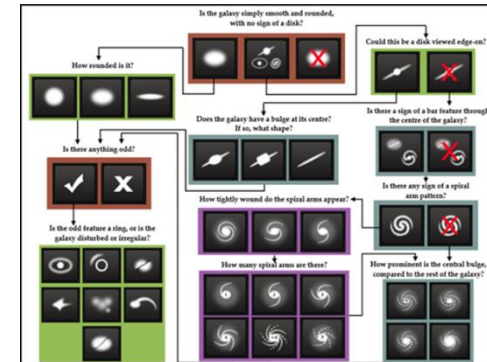
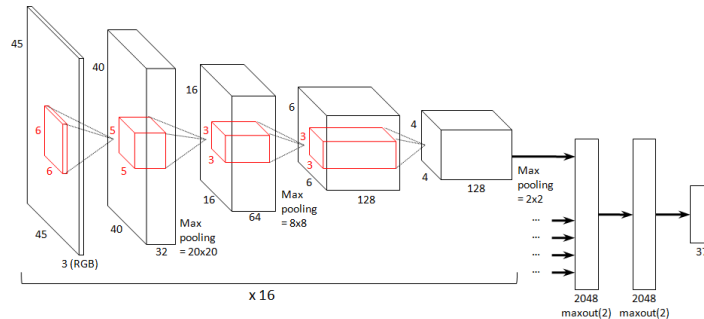
Galaxy Zoo model

Collaboration with Pierre-Alain Duc, Strasbourg Observatory

Structured analysis that integrates prior knowledge

Multi-label classification task [1]

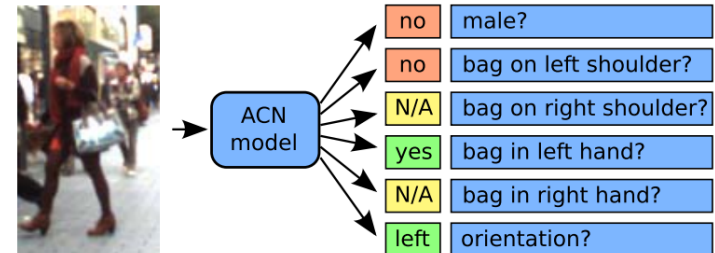
- Rough estimation of numerical attributes
- Does not account for relations between parameters



Hierarchical loss function [2]

$$p(A, B) = p(B|A) \cdot p(A)$$

Visible Value Value term Visibility term



Structured loss for galaxy morphology characterisation (on-going work)

- Combines classification and regression
- Deeper hierarchy, integrate knowledge of correlated attributes

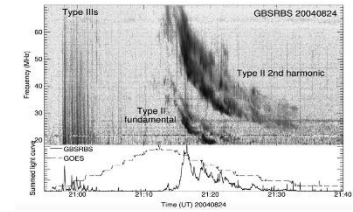
[1] S. Dieleman: **My solution for the Galaxy Zoo challenge**, 5 April 2014. [Online]

[2] P. Sudowe, H. Spitzer, B. Leibe: **Person Attribute Recognition with a Jointly-Trained Holistic CNN Model**. ICCV-W, 2015

The question of representation

- Parametric representation

- Radio burst: duration, decrease rate, thickness...
- Galaxy morphology: number and angle of arms, size of bar...



- Learned representation

- Comets:

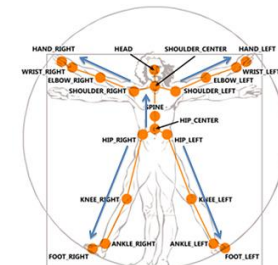
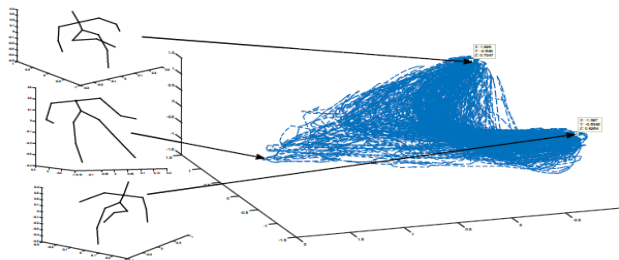
Parametric representation hard to define



- Body pose:

Skeleton (e.g. Kinect) may be more complex than needed

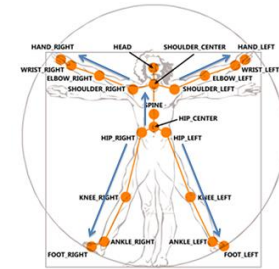
Robust Diffusion Map
Manifold



Kinect
skeleton

The body poses of a (single) movement

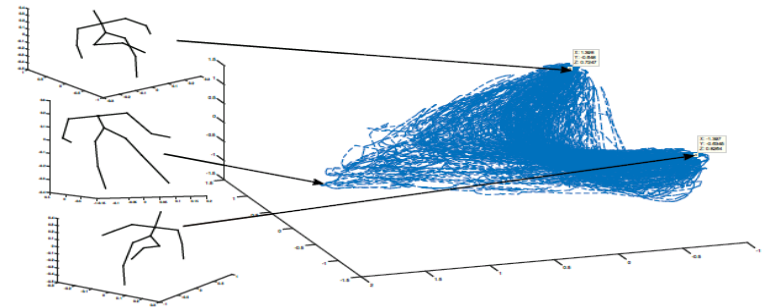
Skeleton representation: redundant and complex



Kinect skeleton

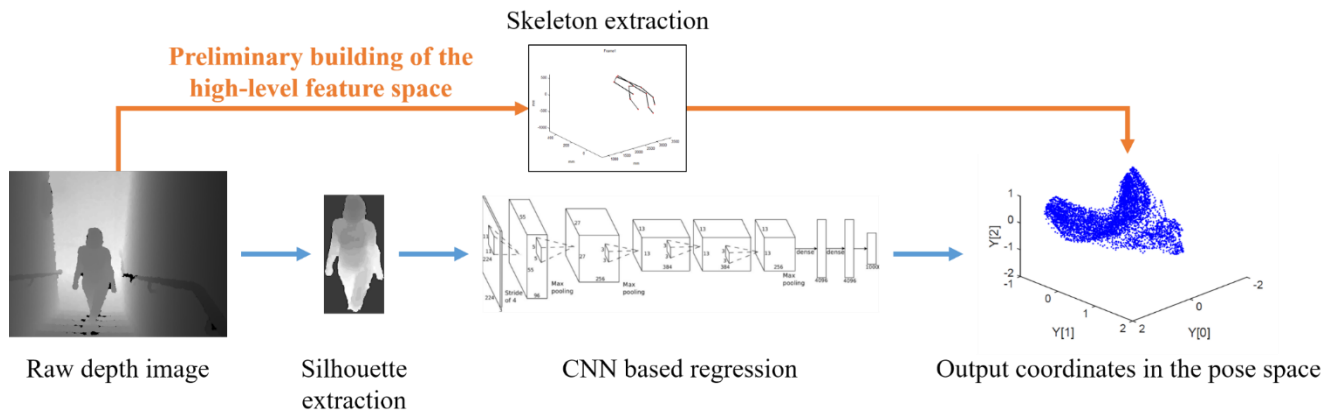
Manifold representation of body pose [1]:

- Capture relevant pose variations



Robust Diffusion Map Manifold

Using the manifold representation:

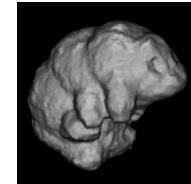
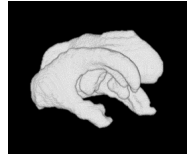
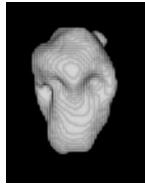


[1] A. Paiement, L. Tao, S. Hannuna, M. Camplani, D. Damen, M. Mirmehdi: **Online quality assessment of human movement from skeleton data**. *BMVC*, 2014

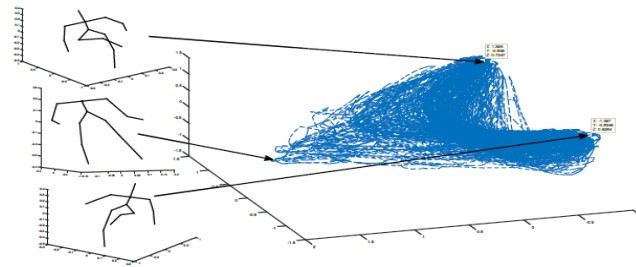
[2] B. Crabbe, A. Paiement, S. Hannuna, M. Mirmehdi: **Skeleton-free body pose estimation from depth images for movement analysis**. *ChLearn Looking at People workshop at ICCV*, 2015

Overview: Characterising shapes and motions

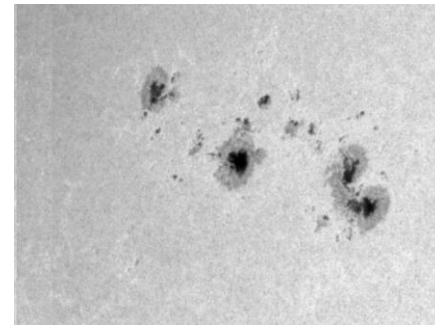
Shape reconstruction



Shape analysis

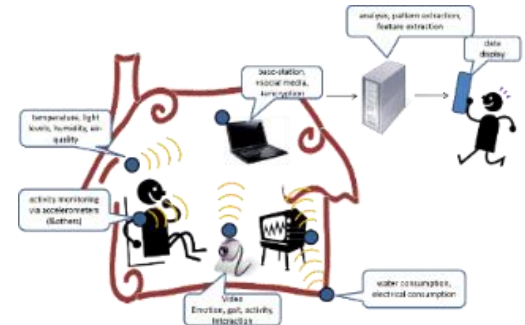
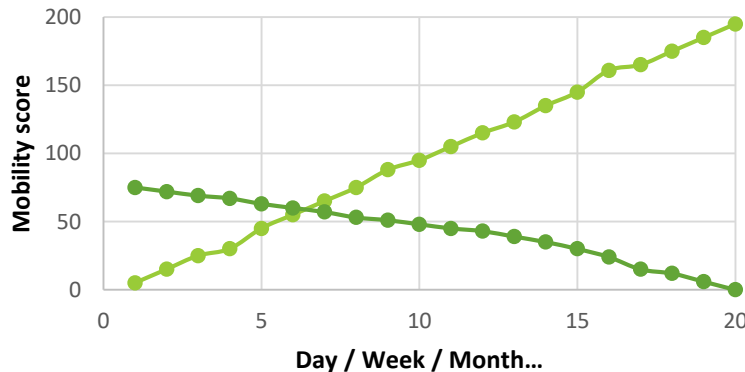


Motion analysis



Mobility assessment from Kinect data

Aim: Continuous **score** for movement quality

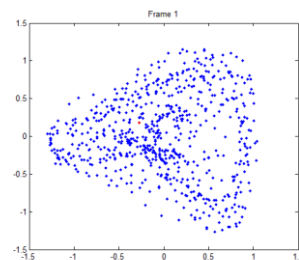


Quantifying deviations to a model of “normal” movement:

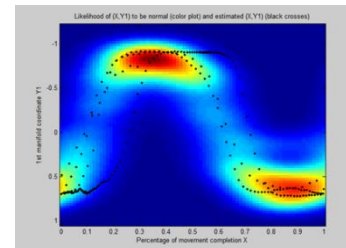
Kinect skeleton data



Pose representation



Statistical model of kinematics



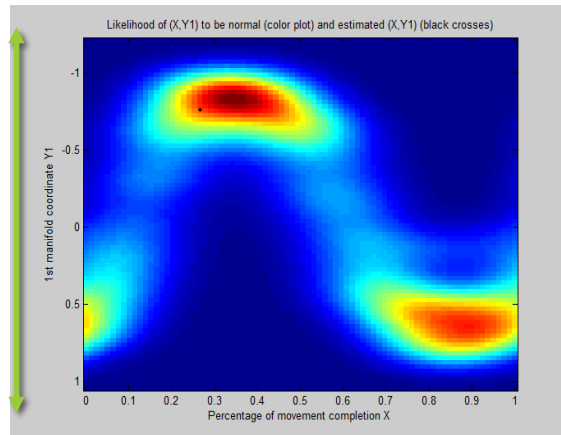
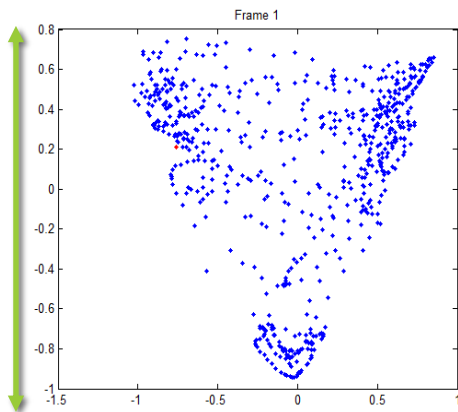
Measure of kinematics' quality

Statistical model of pose

Measure of pose's quality

Mobility assessment from Kinect data

Example of normal movement:

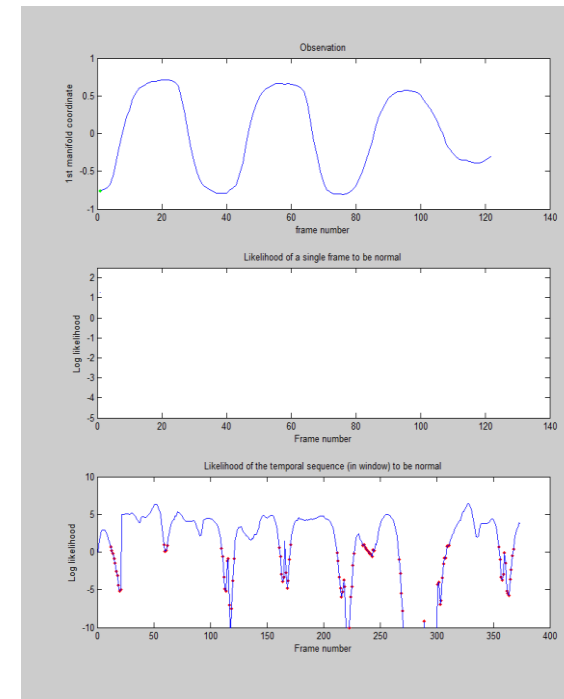


Hidden state x

First manifold coordinate

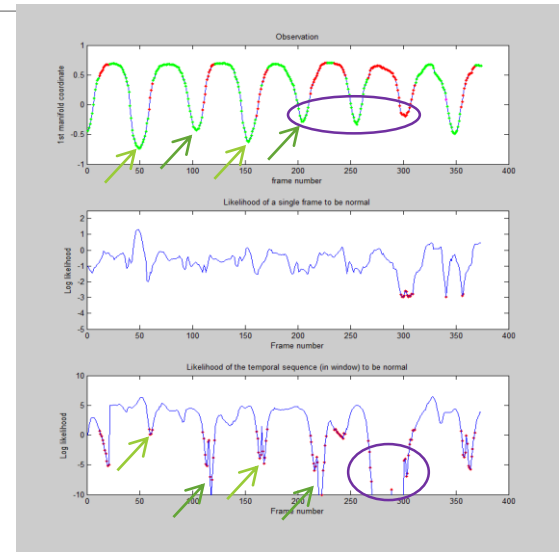
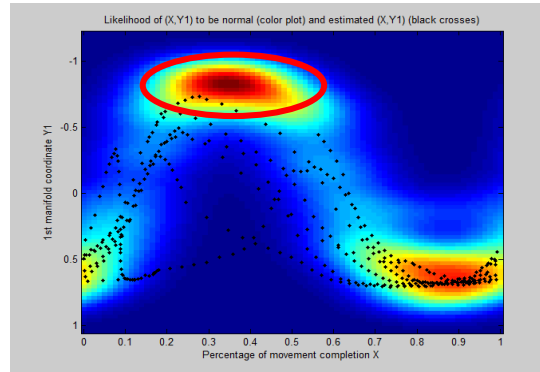
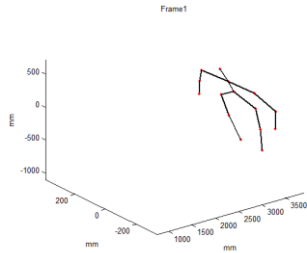
Pose score

Kinematics score

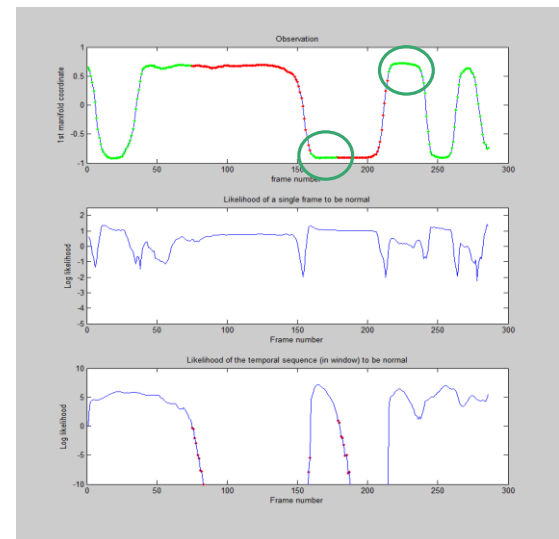
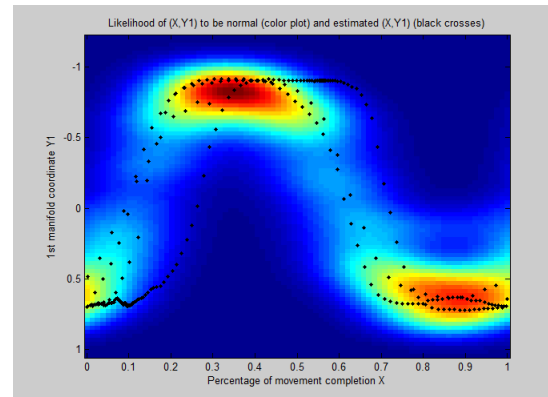


Some abnormal movements

- Left leg lead

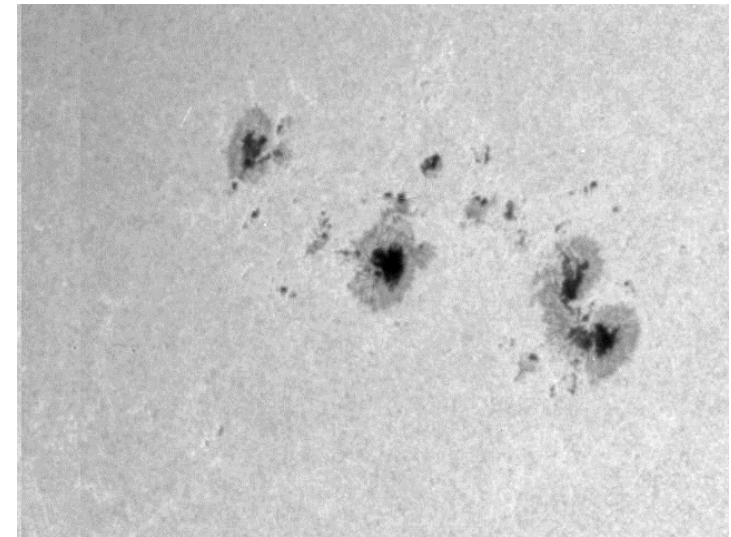
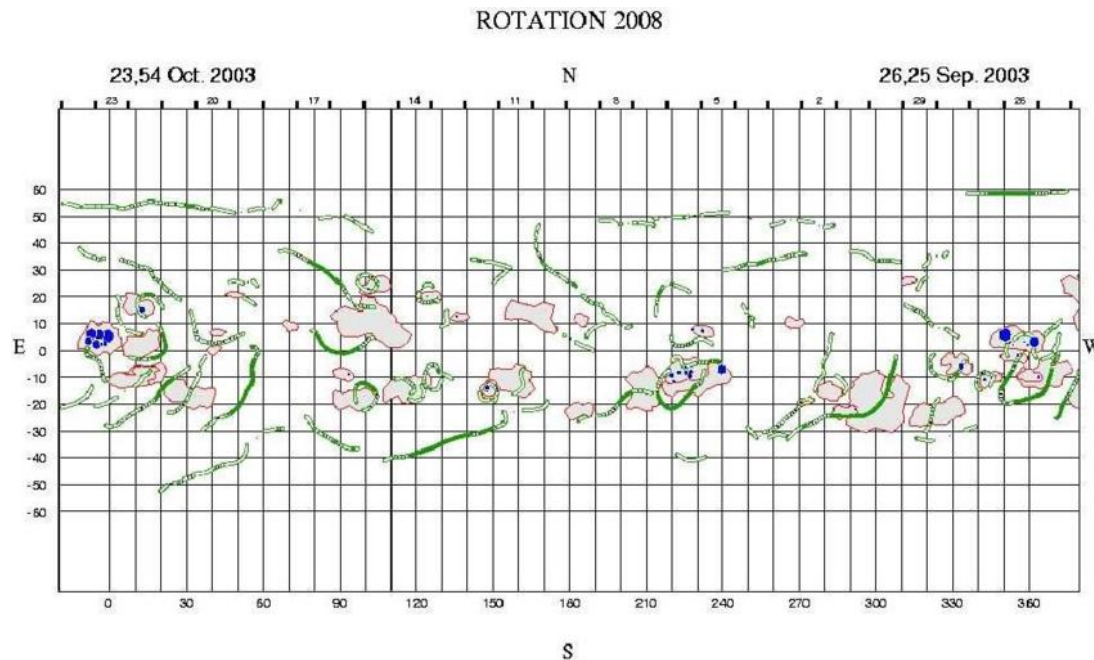


- Freeze



Other application of modelling motions

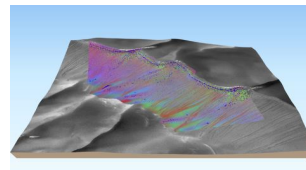
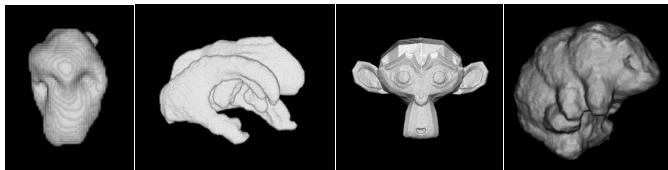
- Behaviours of solar features
 - Discovering families of behaviours?



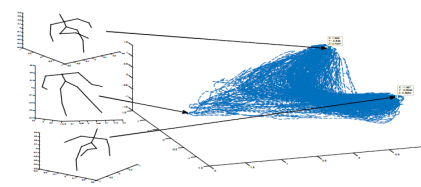
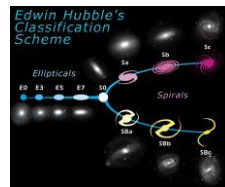
Quick summary

Characterising shapes and motions

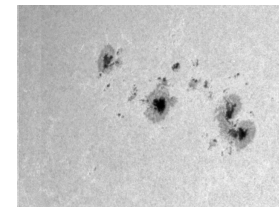
Shape reconstruction

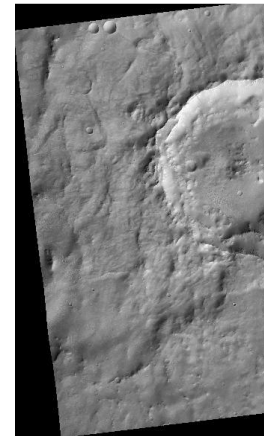


Shape analysis



Motion analysis





Thank you

