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

Scientific image analysis
Similar challenges

Scientific image analysis

- Multimodal images: Different resolutions and modalities / wavelengths
- Gaps
  - spectral
  - spatial
- Misalignments
  - temporal
- 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

Scientific image analysis
Overview: Characterising shapes and motions

Shape reconstruction

Shape analysis

Motion analysis

Scientific image analysis
IReSISD: shape modelling for multimodal data

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


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

IReSISD: shape modelling for difficult data
Some examples of application in astronomy

- Modelling of the Martian terrain from orbital multispectral images
  1. 3D point cloud: stereoscopic photometry
  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

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Scientific image 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 deep neural network**

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

➢ Image enhancement? Adaptive transfer learning?

Galaxy morphology

Joint solving of interdependent tasks:

- Classification of morphology types
- Regression of morphology parameters

Collaboration with Pierre-Alain Duc, Strasbourg Observatory

Shape characterisation
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]
  \[ p(A, B) = p(BIA) \cdot p(A) \]

- Structured loss for galaxy morphology characterisation (on-going work)
  - Combines classification and regression
  - Deeper hierarchy, integrate knowledge of correlated attributes

The question of representation

• Parametric representation
  o Radio burst: duration, decrease rate, thickness...
  o Galaxy morphology: number and angle of arms, size of bar...

• Learned representation
  o Comets:
    Parametric representation hard to define
  o Body pose:
    Skeleton (e.g. Kinect) may be more complex than needed
The body poses of a (single) movement

Skeleton representation: redundant and complex

Manifold representation of body pose [1]:
- Capture relevant pose variations

Using the manifold representation:

- Robust Diffusion Map Manifold

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Scientific image 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**
- **Statistical model of pose**

**Measure of kinematics’ quality**

**Measure of pose’s quality**

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Mobility assessment from Kinect data

Example of normal movement:

First manifold coordinate
Pose score
Kinematics score
Hidden state x
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

Astronomy image analysis
Thank you