浙江大学爱丁堡大学联合学院

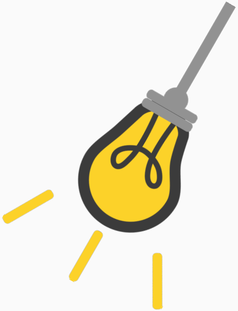
ZJU-UoE Institute

Lecture 09 - Registration and motion tracking

Nicola Romanò - nicola.romano@ed.ac.uk

Learning objectives

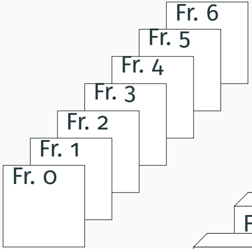
- Describe the challenges related to working with videos
- Describe some of the approaches to video registration
- Describe some of the approaches related to motion tracking



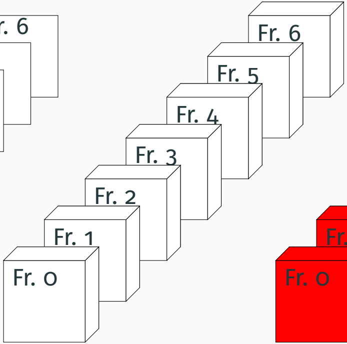
Introduction - working with videos

A video is just a sequence of images, that we can store in a tensor with 3 or more dimensions.

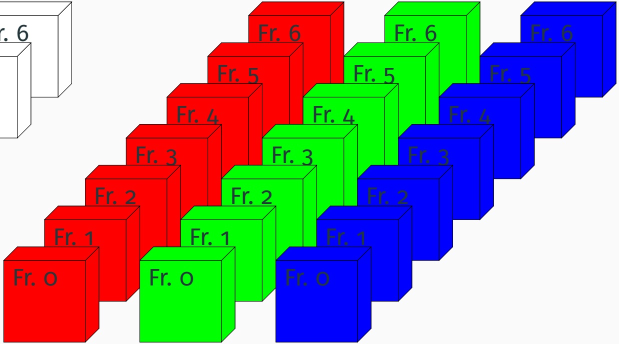
2D video (3D tensor)



Video of 3D stacks (4D tensor)



Video of 3D RGB stacks (5D tensor)

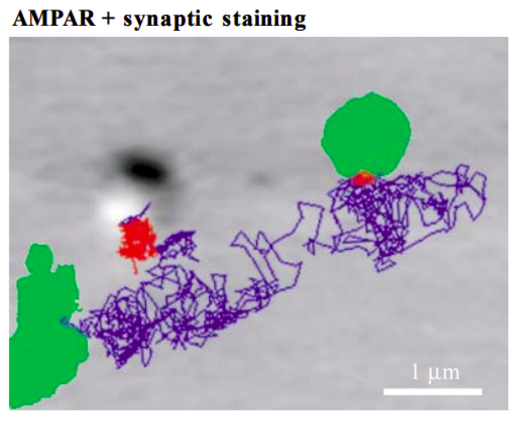


Videos in biomedical imaging

- Many biological processes are dynamic and capturing/analysing them is a challenging task.
- Often tradeoff between acquisition speed and image quality is needed.
- Need analysis methods that are robust to noise and outliers.
- Generally we want to find object(s) of interest in each frame and be able to identify them across frames.

Examples of dynamic biological processes captured in videos.

- Tracking single molecules, vesicles, organelles in a cell



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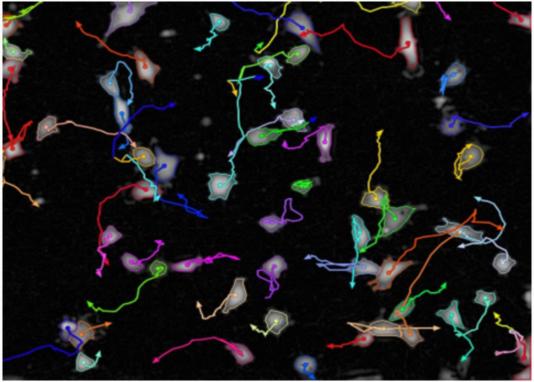
- Tracking cells in a dish or in a tissue

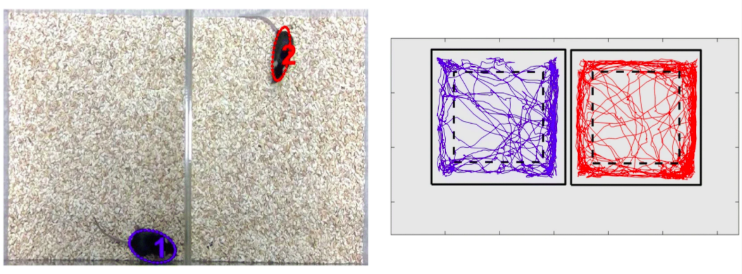


Perkin Elmer - Tracking of cells in a dish.

Some examples

Examples of dynamic biological processes captured in videos.

- Tracking single molecules, vesicles, organelles in a cell
- Tracking cells in a dish or in a tissue
- Tracking a mouse during a behavioural experiment



Mouse tracking in a behavioural experiment.

A general motion tracking pipeline

1. (*optional*) Registration of the video
2. Object detection
3. Object tracking
4. Measurement of object properties over time

Registration

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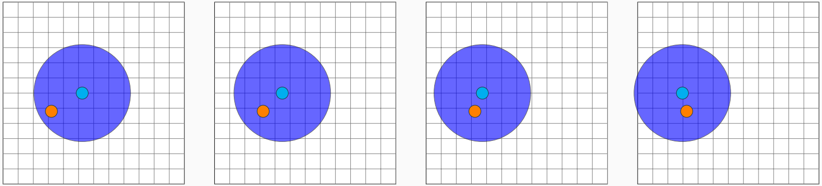
For instance, registration is useful for correcting:

- In vivo imaging where breathing artefacts can shift the field of view
- Drifting of the sample under a microscope
- Aligning MRI from the same subject in different sessions

Registration - motivation

Registration is important because otherwise quantification could be inaccurate.



The orange cell is moving horizontally to the right, while the cyan cell is fixed; because the coverslip is drifting to the left, the coordinates of the orange cell stay fixed, while the cyan cell appers to move to the left.

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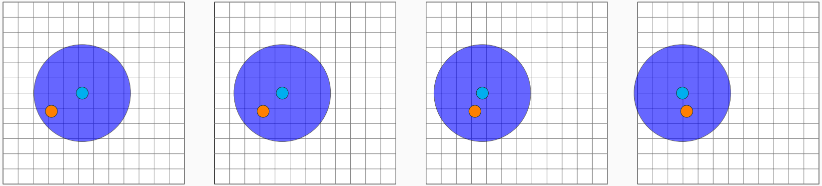

The orange cell is moving horizontally to the right, while the cyan cell is fixed; because the coverslip is drifting to the left, the coordinates of the orange cell stay fixed, while the cyan cell appers to move to the left.

While it is relatively straightforward to correct for this drift, drift in the z-axis is much more complex, as it changes the plane of focus that is being imaged.

Types of registration algorithms

We can classify registration algorithms into

- **Intensity-based** - compare intensity patterns between the reference and the current frame via correlation
- **Feature-based** - find correspondences between features (points, corners etc) in the reference and the current frame
- **Mixed approaches**

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Registration can be performed through:

- **Rigid-body transformations** - translations and rotations only
- **Non-linear transformations** - including affine transformations (scaling, shearing)perspective transformations, curved transformations etc

Rigid-body registration

Rigid-body transformation is the simplest form of registration, consisting only of **translations and rotations**.

Remember from Lecture 2:

Translation

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Rotation

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

We want to find a transformation (translation+rotation) that maps the reference frame to the current frame.

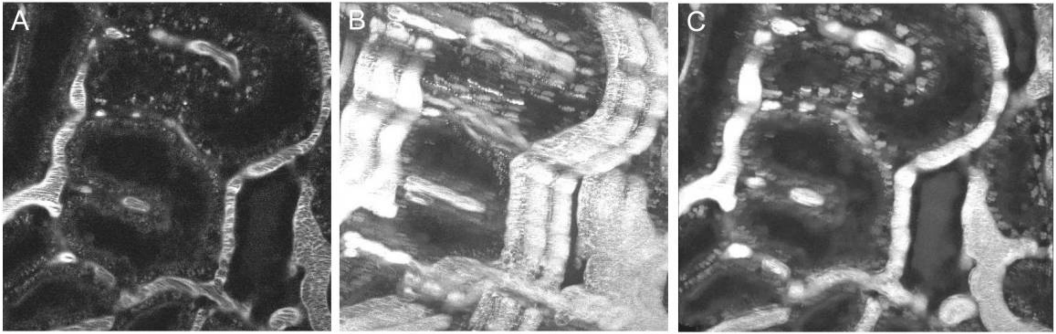
For **intensity-based registration**, given a frame at time t and a reference frame at time t_1, we can find the offset (u, v) that minimizes the MSE:

$$(u, v) = \underset{(u,v)}{\operatorname{argmin}} \sum_x \sum_y (I_{i-1}(x, y) - I_i(x - u, y - v))^2$$

Alternatively, one could maximise the correlation between the two frames:

$$(u, v) = \underset{(u,v)}{\operatorname{argmax}} \sum_x \sum_y (I_{i-1}(x, y) \cdot I_i(x - u, y - v))^2$$

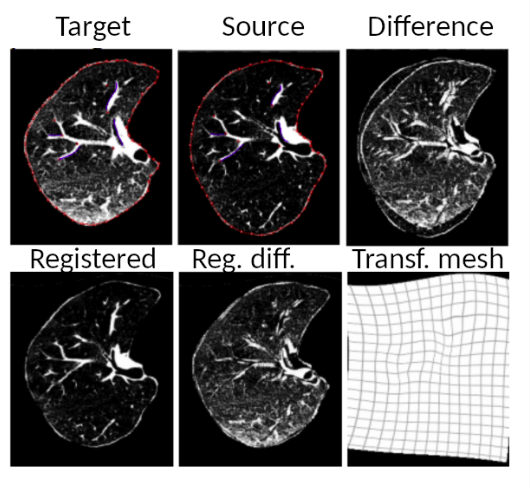
Registration - example



Maximum intensity projection (over the time axis) of a video of kidney vascular flow. Rigid body registration is used to correct for the drift of the sample.

Feature-based registration

Feature-based registration is based on the idea that there are static features in the video, that can be used to match images from one frame to another.



Feature-based non-linear registration of brain MRI images.

Object detection and tracking

Object detection

Object detection in a video is the same process than in a single image.

All the segmentation techniques we have seen so far are applicable in this case as well!

Once we found the object(s) of interest in each frame we want to be able to track them over time.

That is, given n object in a frame, $O_1, O_2, \ldots, O_n$ and n we want to match each of them to the same object in the previous frame.

Nearest-neighbour traking

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- For each detected object we create a window of size w containing it.
- We find the object in the next frame that is closest to the object of interest within that window.
- Improved by predicting the position of the window surrounding the object, based on the displacement in previous frames
- The window could be expanded if no object is found.

Nearest-neighbour tracking can only handle simple situations. For example, it fails if the object disappears for a certain time.

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This type of algorithm works well with relatively sparse and slow moving objects.

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- We compute the histogram for our object of interest
- We then "back-project" the histogram onto the new frame. This means that we take each pixel in the search window and sum the probability of their intensities in the histogram.
- We then try to maximise this probability by shifting the search window.

Measurement of object properties

Measuring cell properties

Just as we saw in the segmentation lecture we can use the `regionprops` function to measure properties of the detected objects.

We will simply measure these properties in each frame by applying the function multiple times.

Furthermore knowing the position of the object(s) in each frame we can calculate their direction and speed.

And now an example!

I will now show an example of analysis of a simple video.