Summaries of a few papers on mitral valve prolapse and cross-modal image registration

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Contents

1 Image registration

1.1 3d Point set registration

1.1.1 Point set to point set: Iterative Closest Point algorithm [Besl and McKay, 1992, Chen and Medioni, 1991]

An algorithm to register two sets of points. The basic principle is that it is easy to register two sets of points if the points are matched in pairs, and hard if they are not. See Algorithm 1.

Algorithm 1 Iterative Closest Point

Input: two sets of points X and Y; "find closest point" procedure; "find best transformation" procedure
Output: a transformation from Y to X
  repeat
    for every point $y \in Y$ **do**
      find the point $x(y) \in X$ that is closest to y
    end for
    find the transformation q that best maps all points in Y to their image in X
    apply q to Y
  until $\sum_{y \in Y} ||q(y) - y|| \leq$ some threshold, or number of iterations $\geq$ some threshold
  return the transformation obtained by composing all the successive transformations

1.1.2 Model to point set: Random Sample Consensus (RanSaC) algorithm [Fischler and Bolles, 1981]

The RanSaC algorithm: fit a model to a set of points. Assumes the model can be fitted using a small number of points, but can also fit "as best as possible" a larger number of points, for instance using least squares. The algorithm is robust to outliers. The algorithm is pretty general, and can be further adapted to a specific setting. It is random, but could possibly be made deterministic. See Algorithm 2.

Algorithm 2 Random Sample Consensus

Input: a set of N points; a model that requires $n < N$ points to instantiate; a tolerance threshold α; a number of points threshold t
Output: an instance of the model
  loop
    select n points at random
    instantiate the model using these n points
    find all points that fit the model within a tolerance error $\leq \alpha$
    if the number of points is at least t **then**
      use all these points to instantiate a new model
      return the new model
    end if
  end loop
  if the loop ended without returning a model **then**
    return failure; or alternatively, the model that fitted the highest number of points within α
  end if

1.1.3 Cross-modal point cloud registration [Huang et al., 2016]

Proposes an algorithm for registration of 3d clouds of points, with more than a thousand points: possibly tens of thousands or millions of points. The two clouds may have been generated using different kinds of sensors, and thus present differences, such as inequal point density or missing parts

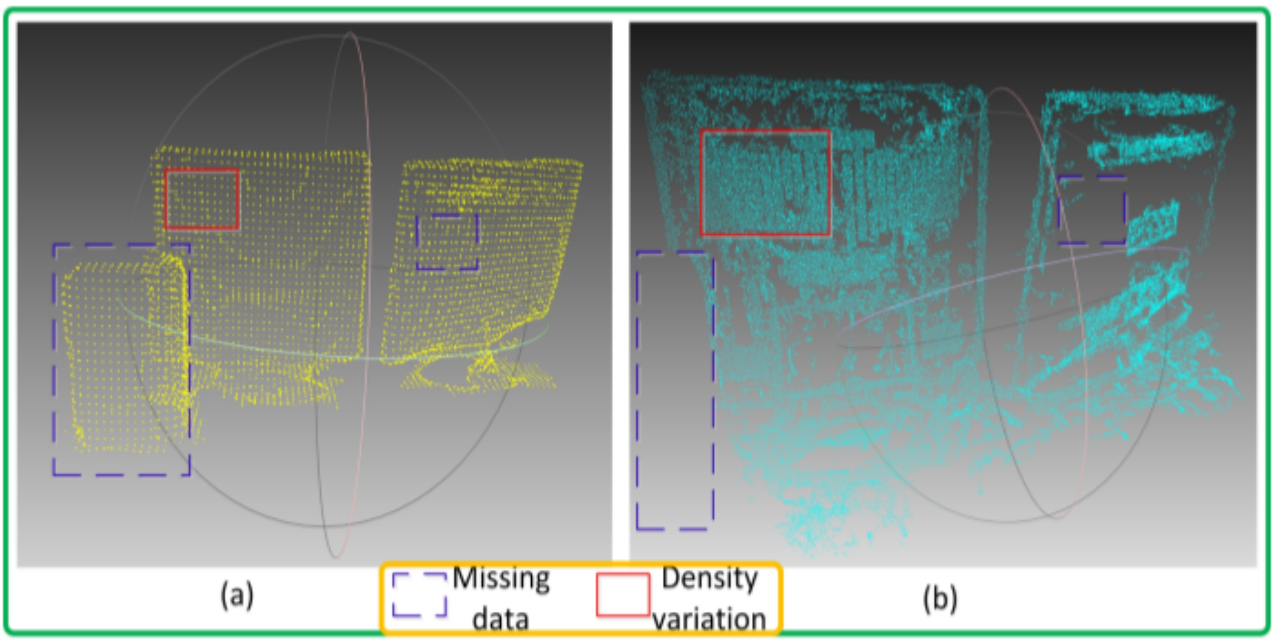

Figure 1: Difference in point density between Kinect (a) and a cloud reconstructed from multiple 2d RGB cameras (b). Illustration from [Huang et al., 2016].

of the represented object: see Fig. 1. The idea behind the algorithm is to extract the "macro" "micro" structures from the images, and use them to build a graph for each image representing those structures. The point cloud registration problem becomes a graph matching problem. The structure extraction algorithm is adapted from a previous paper [Papon et al., 2013]. See Algorithm 3.

Mostly focused on point clouds obtained from these two sources: 1) Kinect; 2) reconstruction from multiple 2D RGB cameras.

Algorithm 3 Point Cloud Registration [Huang et al., 2016]

Input: two 3d point clouds
Output: registration of the two clouds
normalize the scales of the two images
extract the macro and micro structures of each point cloud
build a graph for each point cloud, representing its structure
find best matching between the two graphs
deduce the 3d transformation corresponding to the graph matching
return the 3d transformation

The micro and macro structure extraction consists in clustering voxels (3d pixels) into supervoxels. Look for the sourcecode of the clustering algorithm in the Point Cloud Library [Rusu and Cousins, 2011]. To solve the graph matching problem, see [Zhou and De la Torre, 2013, Cour et al., 2007, Zaslavskiy et al., 2008, Frank and Wolfe, 1956, Gertz and Wright, 2003].

1.1.4 Point cloud registration with outliers [Papazov and Burschka, 2011]

Note that ICP amounts to searching for a rigid transformation T which minimizes the sum of distances between closest points, for two pointclouds D and M:

$$\sum_{x \in D} d(T(x), M)$$

Propose to search instead for a rigid transformation T by minimising instead the sum:

$$\sum_{x \in D} -\varphi(d(T(x), M))$$

where $-\varphi$ is a function which is both increasing and bounded, satisfying $-\varphi(0) = -1$ and $\lim_{d\to+\infty} -\varphi(d) = 0$. The function $-\varphi$ becomes almost constant for large values of the distance d; hence points that are very badly matched cannot have a strong incidence on the minimisation. In a way, the algorithm proposed in this paper is a variant of ICP robust to outliers. It could also be used to detect and remove outliers?

The used formula for φ is:

$$\varphi(d) = \frac{1}{1 + \alpha d}$$

for some parameter α.

The parameter α can be chosen as a function of two parameters d_0 and δ so that $\varphi(d) < \delta$ as soon as $d > d_0$, using the formula:

$$\alpha = \frac{1 - \delta}{\delta {d_0}^2}$$

In their implementation, they choose $\delta = 0.1$ and set d_0 to $1/4$ of the minimum of the three dimensions of the bouding box of the point cloud.

This paper also gives very cool formulae to perform dichotomy on the space of 3d rotations, and to select "uniformly at random" rotations in this space or in the dichotomy subspaces.

1.2 Intensity-based registration

1.2.1 Using intensity for the similarity measure

Need to find more references about this.

Only useful if all images come from the same modality. Usually requires intensity normalization of the two images.

1.2.2 Electron microscopy to light microscopy [Toledo Acosta et al., 2018]

Intensity-based registration, specific for 3d light microscopy (LM) to 3d electron microscopy (EM). The 3d images are stacks; in particular, the size of a pixel in the z-axis differs from the size in the x and y axes.

First, a translation is computed to pre-align the images in the xy-plane, because the misalignment in that plane is expected to be greater than in the z-axis. A 3d region of interest is selected in the stack, by human intervention or by some other algorithm. The light microscopy stack is projected into a 2d image using maximum-intensity projection, while a few slices are selected from the electron microscopy stack. Then each EM slice is aligned to the LM projection, using a rotation-invariant similiarity measure on a histogram-based description of the Laplacian-of-Gaussian of each of the two images. The full LM stack is shifted by a weighted average of the translations corresponding to each EM slice.

Second, a 2d affine transformation is computed to align the 3d LoG-EM-RoI and the pre-aligned 3d LoG-LM-RoI. The LoG-LM stack is resampled with a low-pass filter and a bilinear interpolator, so that pixel size for the two images are the same. The transformation is computed using the similarity measure Mutual Information, and is computed in two steps: first, a rigid transformation, ie, a direct isometry; then, an additional affine transformation.

1.3 Cross-modal registration using image analogies

1.3.1 Generating an image looking like modality B given an image coming from modality A [Hertzmann et al., 2001]

See Fig. 2.

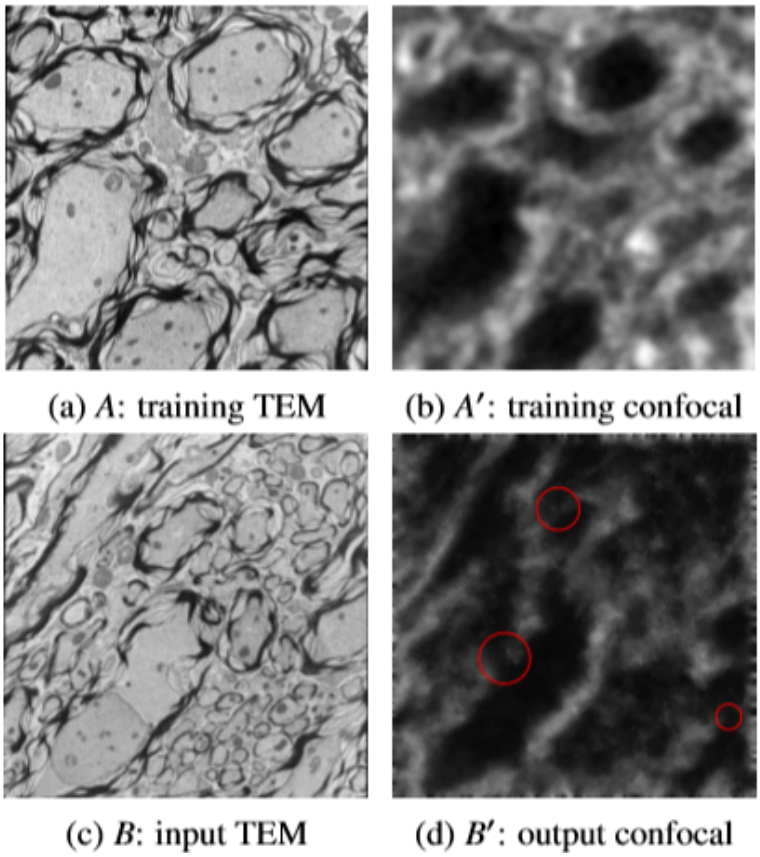

Figure 2: After training on pairs of images coming from two different modalities, the neural network can simulate an image from the second modality when given an image from the first modality. Illustration from [Cao et al., 2014].

1.3.2 Building dictionaries of features [Cao et al., 2014]

Uses machine learning on a training dataset of pairs of images from two different modalities to learn two dictionaries D_A and D_B of small filters for each modality.

To register an image I_A from modality A with an image I_B from modality B: first, the image I_A from modality A is converted into a sparse vector α such that I_A can be reconstructed from vector α and dictionary D_A. Then an image I'_B is constructed from α and D_B. Then images I_B and I'_B can be registered using a uni-modality registration algorithm. See Fig. 3.

1.3.3 How to solve the registration problem with the reconstructed image

1. Denoising the image rebuilt from the dictionary of features [Elad and Aharon, 2006, Li and Liu, 2009] (note: surprisingly, [Cao et al., 2014] does not cite [Li and Liu, 2009]) and denoising the target image

2. "We consider rigid followed by affine and B-spline registrations in this paper and use elastix's implementation [Klein et al., 2010, Johnson et al., 2015]. As similarity measures we use sum of squared differences (SSD) and mutual information (MI). A standard gradient descent is used for optimization. For B-spline registration, we use displacement magnitude regularization which penalizes $||T(x) - x||^2$, where $T(x)$ is the transformation of coordinate x in an image [Klein et al., 2010]. This is justified as we do not expect large deformations between the images as they represent the same structure. Hence, small displacements are expected, which are favored by this form of regularization." [Cao et al., 2014]

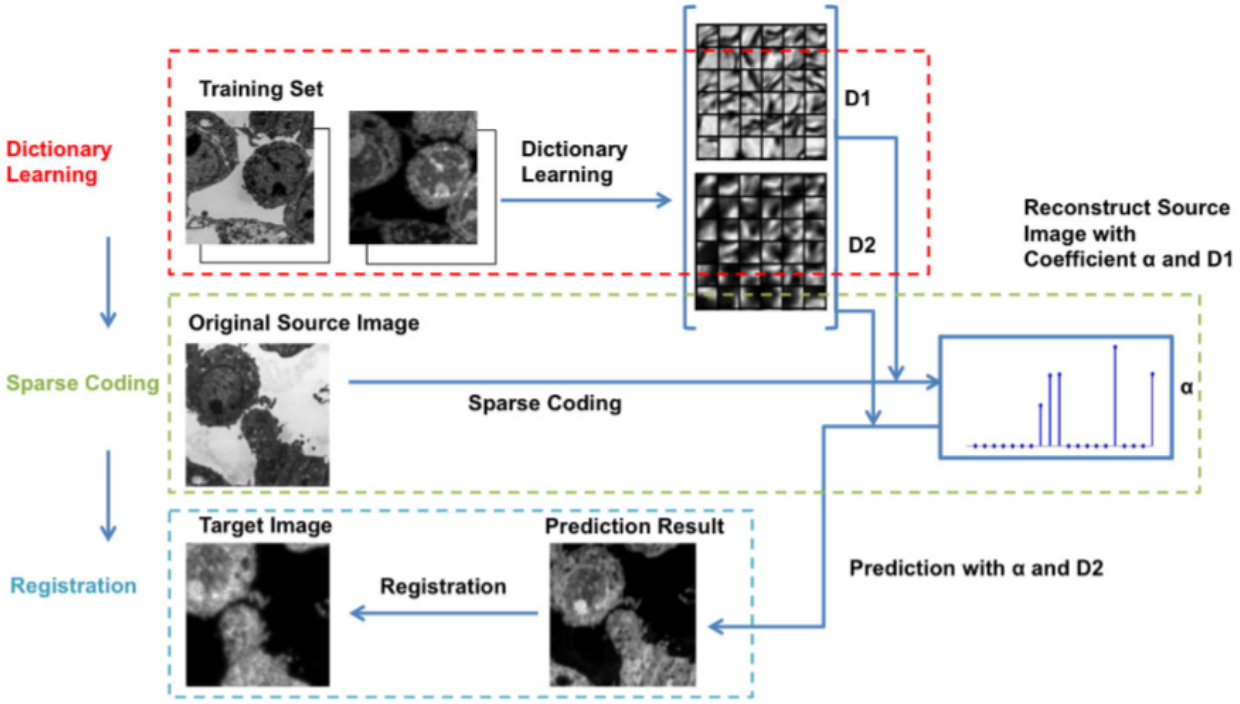

Figure 3: Summary of the registration algorithm using deep learning to extract dictionaries of features. Illustration from [Cao et al., 2014].

1.4 Using similarity measures with deep learning [Litjens et al., 2017]

1.4.1 Extracting features in MR brain images with unsupervised deep learning [Wu et al., 2013]

Proposes an unsupervised deep learning approach to directly learn the basis filters that can effectively represent all observed image patches in magnetic resonance (MR) brain images. The coefficients by these learnt basis filters in representing the particular image patch can be regarded as the morphological signature for correspondence detection during image registration. Specifically, a stacked two-layer convolutional network is constructed to seek for the hierarchical representations for each image patch, where the high-level features are inferred from the responses of the low-level network.

Not multimodal: only MR images. But the training is unsupervised.

1.4.2 Using a convolutional neural network to compute the similarity measure in multi-modal registration [Simonovsky et al., 2016]

Proposes a metric based on a convolutional neural network, to replace Mutual Information as a similarity measure. The network can be trained from scratch even from a few aligned image pairs. The metric is validated on intersubject deformable registration.

Supervised, but requires "only a few" aligned image pairs. Multi-modal?

1.4.3 Using stacked auto-encoders to compute the similarity measure in multi-modal registration [Cheng et al., 2018]

Trains a binary classifier to learn the correspondence of two image patches. The classification output is transformed to a continuous probability value, then used as the similarity score. Proposes to utilise multi-modal stacked denoising autoencoder to effectively pre-train the deep neural network. Train and test the proposed metric using sampled corresponding/non-corresponding computed tomography and magnetic resonance head image patches from a same subject.

Multi-modal: MR and CT.

2 Analysis of cell images

See Fig. 4.

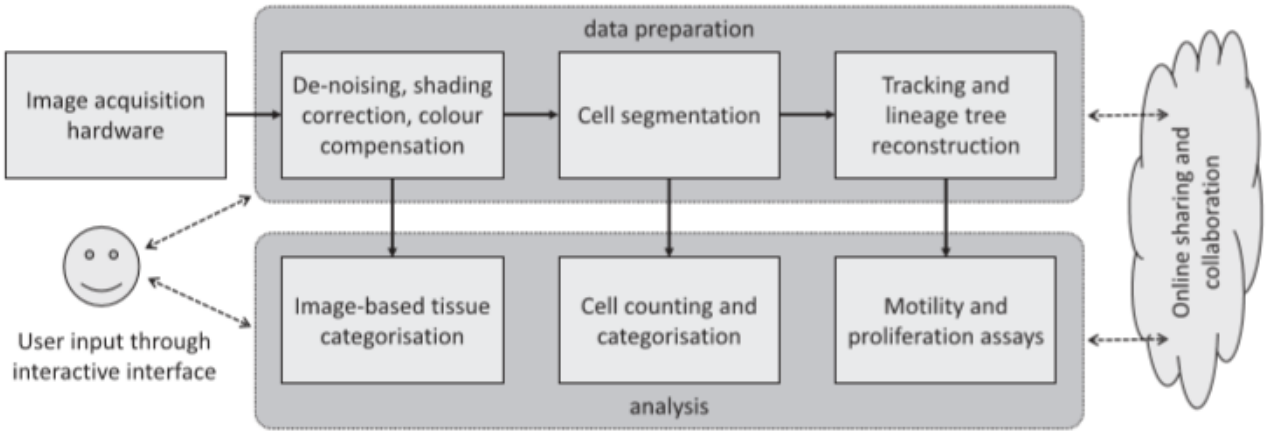

Figure 4: Common tasks in analysis of cell images. Illustration from [Kan, 2017].

2.1 Cell segmentation

2.1.1 Colour threshold and pixel adjacency

Apply filters to remove noise, blur, and non-cell objects. Use an intensity threshold to classify pixels as part of a cell or part of the background. Use connected component analysis to separate non-touching cells. If cells overlap, use a "watershed" technique to separate them.

2.1.2 After segmentation, decision tree to classify an image segment as a cell or not a cell based on its area and elongation [Kan, 2017]

After segmenting the objects in the image, classify each object as a cell or not a cell. Possible features for the classifier:

- area (small objects are not cells);
- elongation $4\pi A/P^2$, where A is area and P is perimeter (close to 1 if object is shaped like a disc, close to 0 if it is shaped like a line).

2.1.3 Convolutional neural networks

2018 Data Science Bowl [Marks, 2018] A contest on kaggle to devise algorithms for cell segmentation. The algorithms are required to be able to handle images from several different experiments using light microscopy. The three best ranked submissions to the contest use convolutional neural networks and perform significantly better than the software CellProfiler, while not requiring the user to spend time configuring the software. The good performance of these solutions appears to come in particular from the succesful use of data augmentation and data preprocessing. See Fig. 5.

2.2 Tracking and constructing lineage trees

Cells are observed over time. Need to track individual cells over time. Cells might overlap in some frames; a cell might divide through mitosis.

2.2.1 Classification problem

Given two successive frames, classify all pairs (cell from first frame, cell from second frame) as "same cell" or "distinct cells" [Kan, 2017]. See Fig. 6.

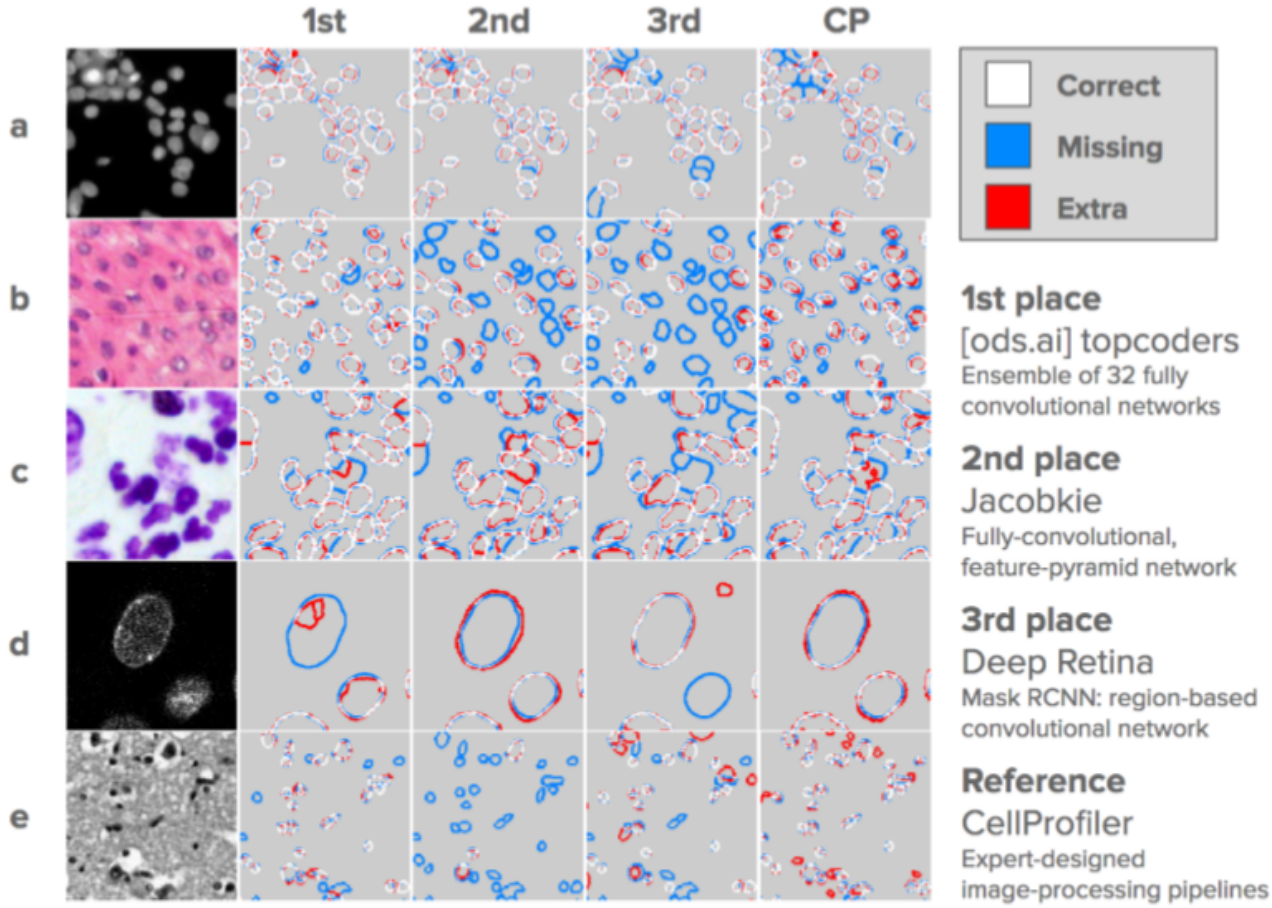

Figure 5: Illustration from [Marks, 2018].

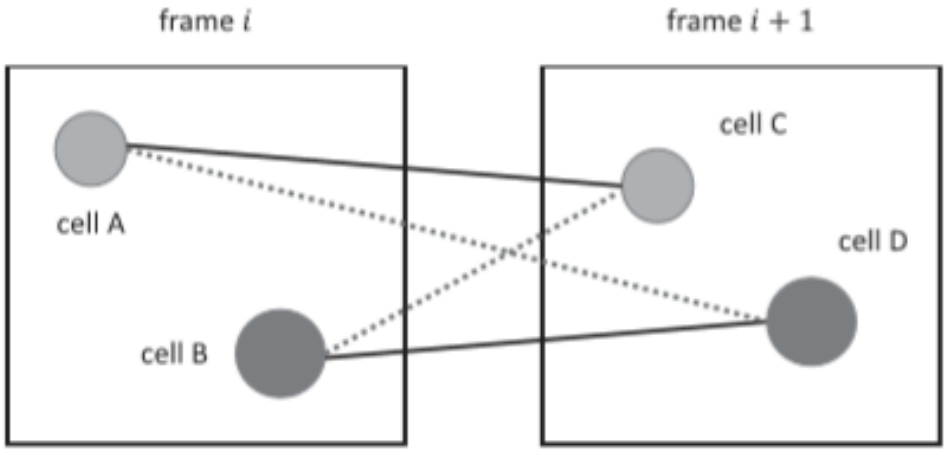

Figure 6: Illustration from [Kan, 2017].

3 Other applications of deep learning in medical imaging [Litjens et al., 2017]

3.1 Classification of images from medical exams

3.2 Content-based image retrieval

Browsing massive databases, for instance retrieving similar case histories. Feature extraction is very useful here.

3.3 Generating text reports from images [Schlegl et al., 2015]

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