## Medical Imaging <br> Lecture: Multi-modal Image Registration

## 1. Image Registration in Medicine



- Registration - a problem common to many tasks in medical imaging: align two or more images. Images can be two dimensional or three dimensional.
- Aspects of registration:
- measured object: intra patient - inter individual (e.g. atlas)
- measuring device: single modality - multi-modal (CT-MRT, MRT-PET,. . . )
- Transformation: rigid body, affine transformation - smooth but non-linear transformation.


## 2. Simple case: single patient, single modality

A. Simplest case We start with the simplest variant: register two images of the same patient acquired with the same sensor:

Images: $u, u^{\prime}$, defined on domains $\mathcal{D}, \mathcal{D}^{\prime}$ respectively, where

- $\mathcal{D}, \mathcal{D}^{\prime} \subset \mathbb{Z}^{2}\left(\mathbb{Z}^{3}\right)$
- $u(\boldsymbol{r})$ denotes the image value at pixel (voxel) $\boldsymbol{r}$.

Task (informal): Find the best alignment of the images.


Task (formal): Find the rotation matrix $R$ and the translation vector $t$ which minimise the sum of squared differences

$$
\left(R^{*}, \boldsymbol{t}^{*}\right)=\underset{R, \boldsymbol{t}}{\arg \min } \frac{1}{|\mathcal{A}|} \sum_{\boldsymbol{r} \in \mathcal{A}}\left[u(\boldsymbol{r})-u^{\prime}(R \boldsymbol{r}+\boldsymbol{t})\right]^{2}
$$

where $\mathcal{A}$ denotes the subset of matched voxels $\mathcal{A}=\left\{\boldsymbol{r} \in D \mid R \boldsymbol{r}+\boldsymbol{t} \in D^{\prime}\right\}$.

## 2. Simple case: single patient, single modality

Problems:

- Points $\boldsymbol{r}^{\prime}=R \boldsymbol{r}+\boldsymbol{t}$ have non-integer coordinates. Image values $u^{\prime}\left(\boldsymbol{r}^{\prime}\right)$ ?
- Criterion depends on the matching region $\mathcal{A}$.

Algorithms:
Here we consider only translations $\boldsymbol{t}$ (for the sake of simplicity)

- Complete enumeration of all possible (integer valued) translations $t$.
- If: image is a "smooth" function and the translation is small as compared with the characteristic length of variation of image values - approximation by Taylor series

$$
u^{\prime}(\boldsymbol{r}+\boldsymbol{t}) \approx u^{\prime}(\boldsymbol{r})+\nabla u^{\prime}(\boldsymbol{r}) \cdot \boldsymbol{t}
$$

The optimisation problem reads

$$
\boldsymbol{t}^{*}=\underset{t}{\arg \min } \frac{1}{|\mathcal{A}|} \sum_{\boldsymbol{r} \in \mathcal{A}}\left[u(\boldsymbol{r})-u^{\prime}(\boldsymbol{r})-\nabla u^{\prime}(\boldsymbol{r}) \cdot \boldsymbol{t}\right]^{2}
$$

## 2. Simple case: single patient, single modality

Let us ignore that $\mathcal{A}$ depends on the translation $\boldsymbol{t}$.

$$
\begin{aligned}
& F(\boldsymbol{t})=\sum_{\boldsymbol{r} \in \mathcal{A}}\left[u(\boldsymbol{r})-u^{\prime}(\boldsymbol{r})-\nabla u^{\prime}(\boldsymbol{r}) \cdot \boldsymbol{t}\right]^{2} \rightarrow \min _{\boldsymbol{t}} \\
& F(\boldsymbol{t})=\sum_{\boldsymbol{r} \in \mathcal{A}}[a(\boldsymbol{r})-\boldsymbol{b}(\boldsymbol{r}) \cdot \boldsymbol{t}]^{2} \rightarrow \min _{\boldsymbol{t}}
\end{aligned}
$$

Find the minimiser by setting the derivative w.r.t. $t$ to zero

$$
\frac{\partial}{\partial \boldsymbol{t}} F(\boldsymbol{t})=2 \sum_{\boldsymbol{r} \in \mathcal{A}}[a(\boldsymbol{r})-\boldsymbol{b}(\boldsymbol{r}) \cdot \boldsymbol{t}] \boldsymbol{b}(\boldsymbol{r})=0
$$

We get

$$
C t-\boldsymbol{d}=0 \quad \Rightarrow \quad \boldsymbol{t}^{*}=C^{-1} \boldsymbol{d}
$$

where

$$
\boldsymbol{d}=\sum_{\boldsymbol{r} \in \mathcal{A}} a(\boldsymbol{r}) \boldsymbol{b}(\boldsymbol{r}) \quad \text { and } \quad C=\sum_{\boldsymbol{r} \in \mathcal{A}} \boldsymbol{b}(\boldsymbol{r}) \otimes \boldsymbol{b}(\boldsymbol{r})
$$

## 3. Transformations and image interpolation

Transformation of pixel (voxel) coordinates $\boldsymbol{r}^{\prime}=T(\boldsymbol{r})$. In coordinates:

$$
\begin{aligned}
x^{\prime} & =T_{x}(x, y) \\
y^{\prime} & =T_{y}(x, y)
\end{aligned}
$$



- Affine transform in $\mathbb{R}^{2}$ is given by $\boldsymbol{r}^{\prime}=A \boldsymbol{r}+\boldsymbol{t}$, where: $\boldsymbol{t}$ - translation vector, $A-2 \times 2$ matrix with non-zero determinant.
- General non-linear transform in $\mathbb{R}^{2}$

$$
\begin{aligned}
& x^{\prime}=f(x, y) \\
& y^{\prime}=x(x, y)=y+\tilde{f}(x, y) \\
&
\end{aligned}
$$

where $f, h$ are general non-linear functions s.t. the Jacobian has everywhere non-zero determinant.

## 3. Transformations and image interpolation

The point $\boldsymbol{r}=(x, y)$ has non-integer coordinates. Which image value $u(\boldsymbol{r})$ should be assigned?

- The point $(x, y)$ is assigned the value of $u$ at the nearest point in the discrete raster.

$$
u(x, y)=u(\operatorname{round}(x), \operatorname{round}(y))
$$

- Linearly combine image values of the 4 neighbouring points

$$
\begin{gathered}
u(x, y)=(1-a)(1-b) u(l, k)+a(1-b) u(l+1, k)+ \\
b(1-a) u(l, k+1)+a b u(l+1, k+1)
\end{gathered}
$$

where

$$
\begin{aligned}
l & =\lfloor x\rfloor,
\end{aligned} \quad a=x-l, ~ 子=\lfloor y\rfloor, \quad b=y-k .
$$




## 4. Multi-modal image registration

- Images $u, v$ defined on domains $D, D^{\prime}$ are captured by different sensors.
- Mean square difference error is not applicable in this case.

Idea: consider the joint histogram of $u$ and the transformed image $v$.

- Images well registered: image values of $u$ and $v$ correlated
- Images not well registered: image values of $u$ and $v$ statistically independent

Let $\hat{v}(\boldsymbol{r})=v(T(\boldsymbol{r}))$ denote the transformed image $v$.
Define the histograms

$$
\begin{aligned}
& p_{u \hat{v}}\left(k, k^{\prime}\right)=\frac{1}{|\mathcal{A}|}\left|\left\{\boldsymbol{r} \in \mathcal{A} \mid u(\boldsymbol{r})=k, \hat{v}(\boldsymbol{r})=k^{\prime}\right\}\right| \\
& p_{u}(k)=\frac{1}{|\mathcal{A}|}|\{\boldsymbol{r} \in \mathcal{A} \mid u(\boldsymbol{r})=k\}|
\end{aligned}
$$

Mutual information

$$
I(u, \hat{v})=\sum_{k, k^{\prime} \in G} p_{u \hat{v}}\left(k, k^{\prime}\right) \log \frac{p_{u \hat{v}}\left(k, k^{\prime}\right)}{p_{u}(k) p_{\hat{v}}\left(k^{\prime}\right)}
$$

We expect $I(u, \hat{v})$ to be maximal for the true transformation $T^{*}$.

## 4. Multi-modal image registration

Let us understand this:

- Let $p(x), q(x), x=1, \ldots, n$ be two discrete probability distributions
- Kullback-Leibler divergence

$$
D(p, q)=\sum_{x=1}^{n} p(x) \log \frac{p(x)}{q(x)}
$$

has property $D(p, q) \geqslant 0$ and $D(p, q)=0 \Leftrightarrow p(x)=q(x) \forall i$

- In our case: $p \Rightarrow p_{u \hat{v}}\left(k, k^{\prime}\right)$ and $q \Rightarrow p_{u}(k) p_{\hat{v}}\left(k^{\prime}\right)$.


## 4. Multi-modal image registration

## Examples:

- $X, Y$ are two independent random discrete random variables: $p(x, y)=p(x) p(y)$. Hence

$$
I(X, Y)=\sum_{x, y=1}^{n} p(x, y) \log \frac{p(x, y)}{p(x) p(y)}=\sum_{x, y=1}^{n} p(x) p(y) \log 1=0
$$

- $X, Y$ are both uniform, i.e. $p(x) \equiv p(y) \equiv \frac{1}{n}$, but strongly correlated, e.g. $p(x, y)=\frac{1}{n} \delta_{x y}$. Then

$$
I(X, Y)=\sum_{x, y=1}^{n} p(x, y) \log \frac{p(x, y)}{p(x) p(y)} \sum_{x, y=1}^{n} \frac{1}{n} \delta_{x y} \log \frac{n^{2}}{n} \delta_{x y}=\log n
$$

## Multi-Modal Registration


source

target

registered source
(Examples from: S. Periaswamy, H. Farid, Elastic Registration with Partial Data, 2003.)

## Discussion:

- Why mutual information?
- Criterion still depends on the matching region $\mathcal{A}$.
- Better results can be obtained if a (probabilistic) anatomical atlas is available.

