

A Method for Automated Landmark Constellation Detection Using Evolutionary Principal Components and Statistical Shape Models

Wei Lu MS Thesis Defense Supervisor: Dr. Hans J Johnson Friday, November 19, 2010 2:00 – 4:00 PM, 4016 Seamans Center



Motivations for automation

- Good news: current imaging technology provides
 - Images with improved spatial resolution
 - High volumes of data
 - Research studies commonly have with hundreds of scans
- Bad news: there is a lot of data 🐑
 - Require increased data processing time
- Therefore: we need automated tools



Motivations – Golden Standard

- Human placement of landmark points (widely used):
 - Labor-intensive (expensive)
 - Subjective
 - Intra/inter-rater inconsistent
 - Not scalable
 - Hard to hire
 - Hard to train
 - Hard to keep busy all the time / or it takes a long time to complete the work



Motivations – Desired Properties

- Computer-aided detection method:
 - Automated (little human efforts required)
 - Efficient (vs. human labeling)
 - Consistent (reproducible)
 - Accurate (similar to human)
 - Generalizable
 - Different modalities
 - Different anatomical regions
 - Robust
 - Noise
 - Orientation
 - Spacing
 - Origin



0 0



Method Overview

Top level data flow diagram





Constellation GUI corrector





11/19/10

Processing Phases

- Landmarks are estimated in a simple to hard, special to general fashion.
- First: find a few reference points/planes
 - Centroid of head mass
 - Mid-sagittal plane transform
 - Eye centers
- Second: most landmarks will be found by a linear model estimation method.





- 1. CoHM is processed first as it can be estimated independently.
- 2. The spatial location is usually stable and very close to the MPJ.













Stop criteria: Until $V_B > V_A$













Compared to center of mass, CoHM is more robust to input image with lots of neck and shoulder portion. That is, CoHM is still very close to MPJ as is expected.

THE UNIVERSITY OF IOWA College of Engineering

Mid-sagittal plane transform estimation



(b)

3D -> 2D, good for base landmark detection



Mid-sagittal plane transform estimation



(b)

Optimal transform: Maximize the reflective correlation in the bounding box centered at CM using Powell's optimizer



Mid-sagittal plane transform estimation



(b) Reflective correlation: Correlation of the intensities of reflected pixels about the MSP and inside the bounding box



Sphere detection using radial Hough transform



Eye detection using radial Hough transform



(a) A typical ROI image for eye centers in (a) axial view, (b) sagittal view, and (c) coronal view

Eye detection demo



(b) A typical accumulator image for eye centers in (a) axial view, (b) sagittal view, and (c) coronal view $% \left({{\mathbf{x}}_{i}} \right)$

Diameter of eyes: 24 mm [1]



Eye detection using radial Hough transform



(a) A typical ROI image for eye centers in (a) axial view, (b) sagittal view, and (c) coronal view

Eye detection demo



(b) A typical accumulator image for eye centers in (a) axial view, (b) sagittal view, and (c) coronal view

ROI: truncated spherical sector

 $R_1 = 120 mm$, $R_2 = 30 mm$, Spread angle = 2.4 rad



Verification for Eye detection



Distribution of IPD for the entire ANSUR database [1]

Wei Lu MS Thesis Defense



11/19/10[1] Figure courtesy of Neil A. Dodgson, Proc. SPIE Vol. 5291

Eye detection using radial Hough transform



Eye detection failure case



Wei Lu MS Thesis Defense

11/19/10

Linear model prediction



Morphometric constraining

1. Human brains share a similar angle from $\overrightarrow{CEC} - \overrightarrow{MPJ}$ to $\overrightarrow{4VN} - \overrightarrow{MPJ}$

2. Human brains share a similar angle from $\overrightarrow{CEC} - \overrightarrow{MPJ}$ to $\overrightarrow{ac} - \overrightarrow{MPJ}$

3. Human brains share a similar $||\overrightarrow{4VN} - \overrightarrow{MPJ}||$

- 4. Human brains share a similar $||\vec{ac} \vec{MPJ}||$
- 5. 4VN is always below the $\overrightarrow{MPJ} \overrightarrow{CEC}$ line on the EMSP plane
- 6. ac is always above the \overrightarrow{MPJ} \overrightarrow{CEC} line on the EMSP plane
- 7. The CEC, MPJ, 4VN, ac and pc are all very close to the EMSP plane
- 8. Nearby landmarks share a linear relationship in location



Morphometric constraining



The information of CEC improves the robustness for ac and 4VN detection



11/19/10

Linear model estimation using Evolutionary PCA

- The relationship between each new landmark is trained by a linear combination of its principal components extracted from the landmarks appearing before it in the processing list.
- New landmarks are estimated one by one, evolutionarily taking the advantage of knowing more information.
- Exploit PCA to extract the most efficient basis to represent a new landmark vector. (scalable)



Physical vector space



Precondition: Some of the landmarks (e.g. LE, RE, AC, PC, and MPJ) have been estimated well in physical space.

Postcondition: Locations of a list of new landmarks (e.g. 4VN, genu, etc.) are estimated reasonably.



Principal component space



All the landmark vectors are transformed into their principal component space.

$$Z = W^{T}X$$

$$W_{opt} = [W_{1}, W_{2}, ..., W_{r}]$$

$$w_{i} := eig(cov(X), i),$$

$$\forall i \in \{1, 2, ..., r\}$$



Principal component space



New landmark (e.g. 4VN) location is estimated by its morphometric relationship among current PCs we obtained in the training phase.



Principal component space



Minor correction are made by local search process.



Physical vector space



Revolutionarily/iteratively add newly estimated landmarks vector (e.g. 4VN) to the physical vector space.

Other new landmarks such as genu can be estimated in a similar way but with additional information from previously estimated landmarks (e.g. 4VN).



Local search estimation



- Template matching: dot product
- Reduce anisotropic error: ten uniformly-rotated copies
- Shape: Cylinder V = $\pi x R^2 x h$
- Size (*mm*): R = 5, h = 10 (salient precise anatomical definition) R = 8, h = 16 (quasi – regional extrema)



Example: Center slices of a T₁-weighted AC template





Constellation distribution









Constellation distribution in sagittal view





Error residuals using LME-EPCA in sagittal view



Detection process review





The input image





Precondition: none **CM** by Otsu thresholding and a topdown maximum sphere radius estimation (CM is used as a reference point to find MPJ when relatively few information is obtained)





Precondition: LE and RE are reasonably found by the radial Hough transform

Center of eye centers (**CEC**) is used as a reference point to guide the search when there is some rotation along Laxis in a LPS coordinate system.





Precondition: CM is correct **MPJ** by a correlation based local search which is centered at CM plus average CM-to-MPJ vector from statistical shape model (SSM)





Precondition: CM is correct **MPJ** by a correlation based local search which is centered at CM plus average CMto-MPJ vector from statistical shape model (SSM)





Precondition: CM is correct **MPJ** by a correlation based local search which is centered at CM plus average CM-to-MPJ vector from statistical shape model (SSM)





Precondition: the estimated CEC and MPJ are reasonable The estimation of **4VN** starts with the morphometric constraints among CEC, MPJ, and 4VN





Precondition: the estimated CEC and MPJ are reasonable The estimation of **4VN** starts with the morphometric constraints among CEC, MPJ, and 4VN





Precondition: the estimated CEC and MPJ are reasonable The estimation of **4VN** starts with the morphometric constraints among CEC, MPJ, and 4VN. A local search is performed near the search center.





Precondition: the estimated CEC and MPJ are reasonable The estimation of **AC** starts with the morphometric constraints among CEC, MPJ, and AC. A local search is performed near the search center.





Precondition: the estimated CEC and MPJ are reasonable The estimation of **AC** starts with the morphometric constraints among CEC, MPJ, and AC. A local search is performed near the search center.





Precondition: the estimated CEC and MPJ are reasonable The estimation of **AC** starts with the morphometric constraints among CEC, MPJ, and AC. A local search is performed near the search center.





Precondition: the estimated AC, MPJ, and 4VN are reasonable **PC** is estimated by a linear model among landmarks





Precondition: the estimated AC, MPJ, and 4VN are reasonable **PC** is estimated by a linear model among landmarks





Precondition: the estimated AC, MPJ, and 4VN are reasonable **PC** is estimated by a linear model among landmarks





Other landmarks are estimated in a way similar to what we have demonstrated in "EPCA demo"



Result



Constellation detection result

		T_1 Images		T_2 Images	
	Landmark Name	Mean	\mathbf{Std}	Mean	\mathbf{Std}
Base	ac	0.97	0.14	1.11	0.54
	pc	1.05	0.76	1.51	0.80
	MPJ	0.78	0.47	0.85	0.33
	4 VN	0.96	0.33	1.34	0.48
Midbrain	aq-4V	1.20	0.43	1.16	0.36
	genu	2.64	2.36	3.18	2.20
	rostrum	2.47	1.57	2.25	1.49
	BPons	1.89	1.20	2.02	0.89
	$optic_chiasm$	2.72	2.15	2.79	1.61
Off-midbrain	$l_ventricular_head$	4.10	3.99	4.38	3.04
	$r_ventricular_head$	2.80	1.68	3.69	2.03
	l_corp	5.73	5.39	6.65	4.09
	$r_{-}corp$	3.68	3.55	4.96	3.56
	l_horiz_ant	6.83	5.60	8.80	4.82
	r_horiz_ant	7.12	4.95	7.83	4.82
	l_sup	8.06	3.77	8.14	4.66
	r_sup	6.71	4.40	7.32	4.59

Average detection errors in mm

Validation for landmark detection accuracy

10 training datasets 10 test datasets



Constellation detection result

Average detection errors in %

Name	mean	\mathbf{std}	
aq-4V	0.38	0.57	
genu	0.30	0.04	
rostrum	0.36	0.23	
BPons	0.42	0.17	
$optic_{-}chiasm$	0.09	-0.48	

(a) Improvement made by local search (in %) for several midbrain landmarks in T_1 images

Name	mean	\mathbf{std}	
$l_ventricular_head$	0.27	-0.16	
$r_ventricular_head$	0.33	0.08	
$l_{-}corp$	0.19	-0.74	
$r_{-}corp$	0.35	-0.16	
l_horiz_ant	0.21	-0.51	
r_horiz_ant	0.06	-0.30	
l_sup	0.05	-0.07	
r_{-sup}	0.01	-0.02	

(b) Improvement made by local search (in %) for several off-midbrain landmarks in T_1 images

Validation for landmark detection accuracy

10 training datasets10 test datasets



Constellation detection result

Average detection errors in mm

Name \mathbf{L} Ρ \mathbf{S} 0.530.480.45ac0.421.470.62pc0.734VN0.610.93

(a) T_1 peg_MR datasets (215 subjects)

Name	\mathbf{L}	Р	S	
ac	0.46	0.73	0.50	
pc	0.34	1.02	1.14	
4 VN	0.50	0.89	0.95	

(b) T_1 AV_MR datasets (98 subjects)

Validation for landmark detection accuracy

20 training datasets



Inconsistency in human placement of landmarks



Validation for landmark detection reliability

20 training datasets

35% error > 2 mm





Moving image with fixed landmarks

Fixed image with fixed landmarks

Warped image with fixed landmarks

TPS warping result







Rigid, 206 subjects, 3 landmarks



TPS, 206 subjects, 41 landmarks





Rigid, 206 subjects, 3 landmarks



TPS, 206 subjects, 41 landmarks

Notice the regions near 4th ventricle, primary fissure, ventricular head, etc





Rigid, 206 subjects, 3 landmarks



TPS, 206 subjects, 41 landmarks

Notice the regions genu, rostrum, optic chiasm, basal pons, cornea, boundary between brains and skull, etc



Conclusion

- This work explored one automated, consistent, and efficient way of estimating landmark constellation by
 - landmark morphometrics + image intensity
 - Principal components + statistical shape models



Conclusion

The proposed method is

- Accurate (salient landmarks)
- Scalable (by EPCA)
- Generalizable
 - Different modalities
 - Different anatomical regions (EPCA algorithm)
- Robust
 - Orientation
 - Spacing
 - Origin

- Thank you!
- Questions?

