Peripheral Nerve Segmentation in Ultrasound Images: a Comparison Between Image Processing Technique and Bayesian Non Parametric Model.

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Motivation

- Cases related to chronic pain, illness or surgical interventions[1].
- These procedures assisted with ultrasound images [2].
- The lack of intelligibility due to speckle noise and artifacts[3].
- Anesthesiologists must have a high level of expertise.
- Epidural needle puncture can lead to paraplegia, paralysis, paresis, and neuropathic pain.

Data Base

- Database recorded in DICOM format, resolution of 640x480 pixels.
- The anesthesiologist labeled 75 images with a NanoMaxx device.[1]

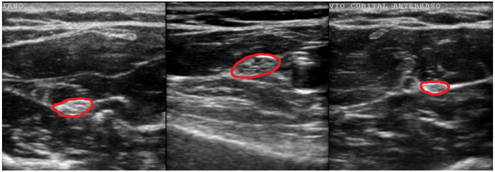


Figure: Nerves: median (left), peroneal (middle) and ulnar (right).

[1] http://www.sonosite.com/products/nanomaxx

Active Shape Model Pipeline

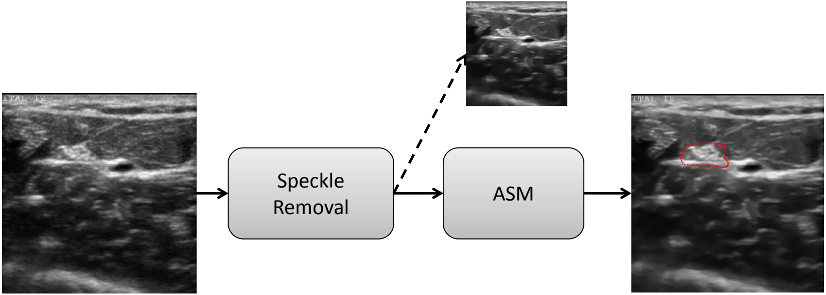


Figure: Pipeline. Speckle removal by NL-Means filter [3], then the ASM warps its contour.

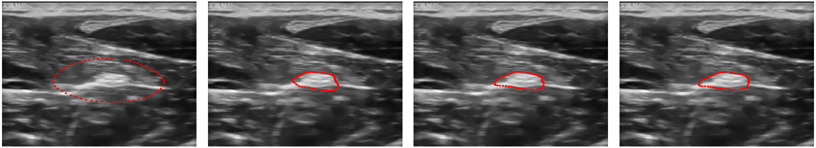
ASM derivation:

- *Procrustes*: Align dataset in a common coordinate system [4].
- Principal Component Analysis (PCA) to retain maximum variance.
- The original data can be approximated with

$$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{P}\mathbf{b},$$

where $\bar{\mathbf{x}} = (x_1, y_1, ..., x_n, y_n)^T$ is the mean form,
$\mathbf{P} = (\mathbf{p}_1, \mathbf{p}_2, ..., \mathbf{p}_t)^T$ is the matrix with first t eigenvalues,
$\mathbf{b} = (b_1, b_2, ..., b_t)^T$ shape parameters vector.

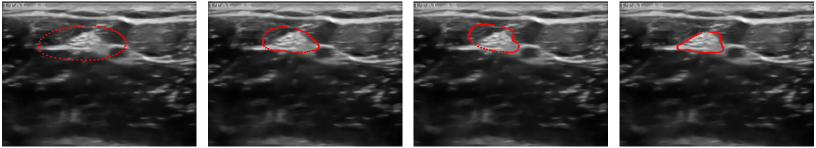
ASM Results I



(a) (b) (c) (d)

Figure: For median nerve: fitting in 1, 5, 50 y 150 iterations.

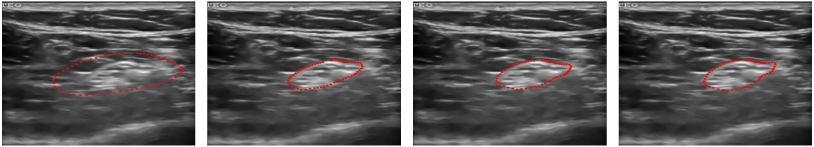
ASM Results II



(a) (b) (c) (d)

Figure: For ulnar nerve: fitting in 1, 5, 50 y 150 iterations.

ASM Results III



(a) (b) (c) (d)

Figure: For peroneal nerve: fitting in 1, 5, 50 y 150 iterations.

Non Parametric Bayesian Model

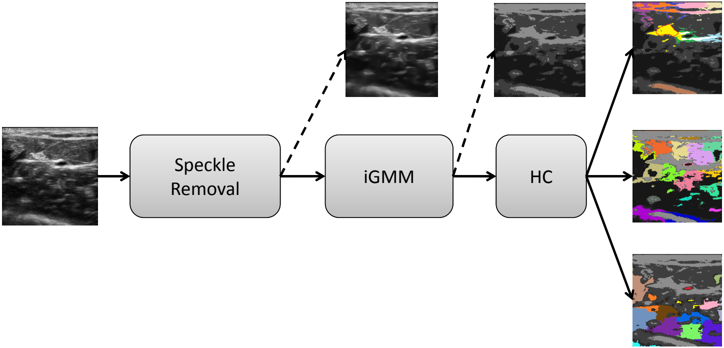


Figure: Pipeline. First speckle removal. The iGMM models image histogram. Finally, Hierarchical clustering nests information.

Non Parametric Bayesian Model I

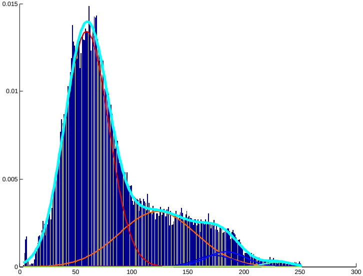
iGMM derivation: comes from Gaussian Mixture Model (GMM)[5]:

$$p(y|\mu_1,...,\mu_k,s_1,...,s_k,\pi_1,...,\pi_k) = \sum_{j=1}^{k} \pi_j \mathcal{N}(\mu_j, {s_j}^{-1}),$$

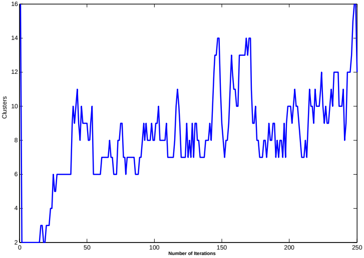
where the analysis suggests to explore the limit when $k \to \infty$.

Therefore, some priors emerge following a Chinese Restaurant Process[6].

Histogram modeled by iGMM



(a)



(b)

Figure: Median nerve histogram modeled by iGMM (left). Inference for number of clusters vs iterations (right).

Classical Hierarchical Clustering

Hierarchical Clustering (HC) is a method that nests data points inside clusters[7]:

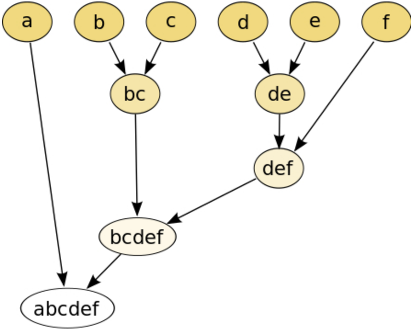
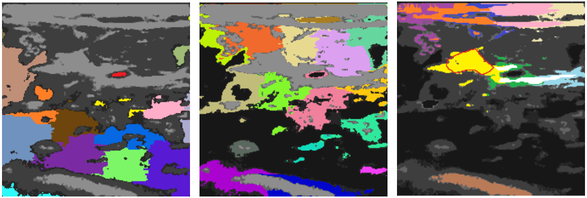


Figure: Graphical example for HC.

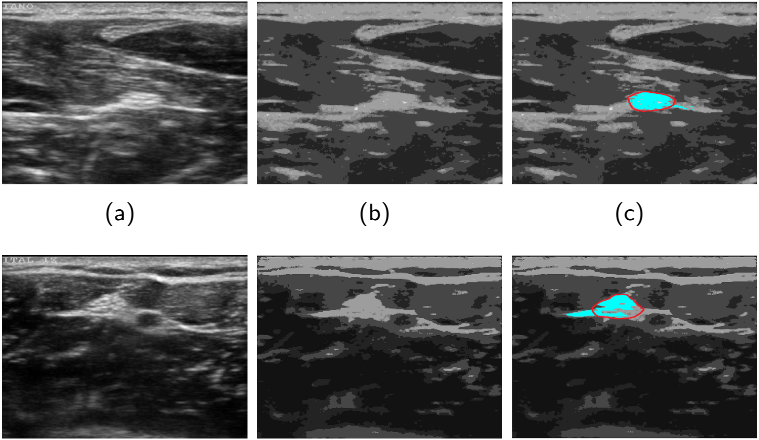
NPBHC Results



(a) (b) (c)

Figure: Results of NPBHC model. Artery (Red), Muscles and Aqueous tissues (others). Middle: Acoustic Shadow (Purple and Blue), Muscles and Aqueous tissues (others). Right-hand: Nerve Structure (Yellow), artery contour, skin and fat (others).

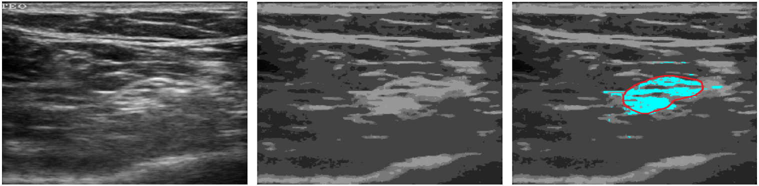
NPBHC Results I



(a) (b) (c)

(d) (e) (f)

NPBHC Results II



(g) (h) (i)

Figure: Results of iGMM and HC. Original image (left), Segmentation by iGMM (middle). Cyan color is ROI found out by the model.

Joint Results I

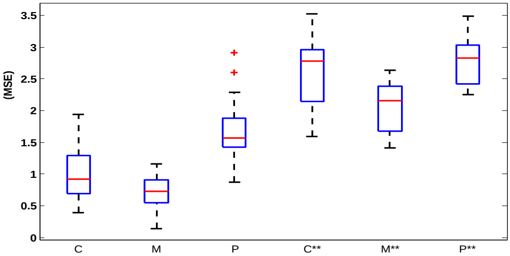


Figure: Segmentation MSE for ulnar (C), median (M) and peroneal (P) nerves. Symbol $**$ means ASM model, and others belong to NPBHC.

Publications

The development of this work allowed us to publish:

- *Peripheral Nerve Segmentation Using Speckle Removal and Bayesian Shape Models*. Hernán F. García, Juan J. Giraldo, Mauricio A. álvarez, álvaro Orozco, y Diego Salazar. Lecture Notes in Computer Science Series, volume 9117, pages 387-394. Springer International Publishing, 2015. IbPRIA 2015: 7th Iberian Conference on Pattern Recognition and Image Analysis.
- *Peripheral Nerve Segmentation using Nonparametric Bayesian Hierarchical Clustering*. Juan J. Giraldo, Mauricio A. álvarez y álvaro A. Orozco. The 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE EMBC 2015, Milan, Italy.

Thanks!

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Bibliografía II

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