Multiscale Medial Shape-Based Analysis of Image Objects

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Invited Paper

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I. Medial Representations

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V. Statistical Shape Characterization via Medial Representations

I. MEDIAL REPRESENTATIONS

we desire that the resulting models be useful for the following:

- statistical characterization of the geometry of a class of object(s) [18] (see Section V);
- segmentation by deforming a model into image intensity data (see Section III-A);
- segmentation by measuring the fit of the local primitive from which the representation is formed to image data either so that
  - ridges of this measure can be used to define the object (cf. Canny edges) (see Section III-B);
  - local statistics of this measure can be used to locate an object section and find its geometric type (slab, tube, sphere) (see [26]).

I. Medial Representations

3-D medial models particularly fit the bill because of a variety of properties that they have, most especially the following.

1) Their inherent geometry provides an object-intrinsic coordinate system and, thus, provides positional and orientational correspondence between instances of the object in and near the object(s).
2) They directly capture the object interior in a compact way and are, thus, computationally suitable for volumetric deformation.
3) They provide the basis for an intuitive object-based multiscale sequence leading to efficiency of segmentation algorithms and trainability of statistical characterizations with limited training sets.

I. Medial Representations

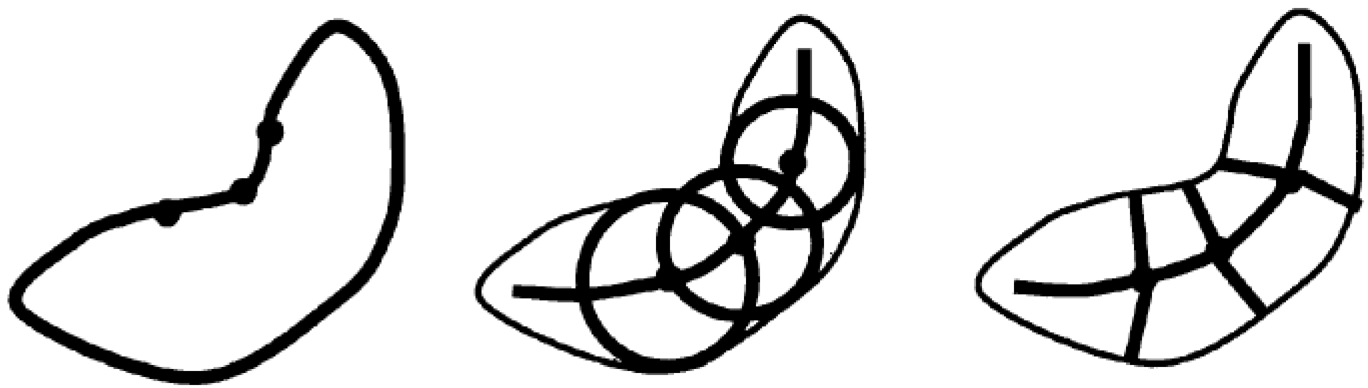


Fig. 1. 2-D figure shown in terms of its boundary, then in terms of bitangent circles wholly interior to the figure, and finally, in terms of medial atoms (see also Fig. 5 for the 3-D case). Individual positions, circles, and medial atoms are shown at sample positions, but in each case, the locus is continuous. The part of this figure that forms the representation is shown in each case with bolder lines.

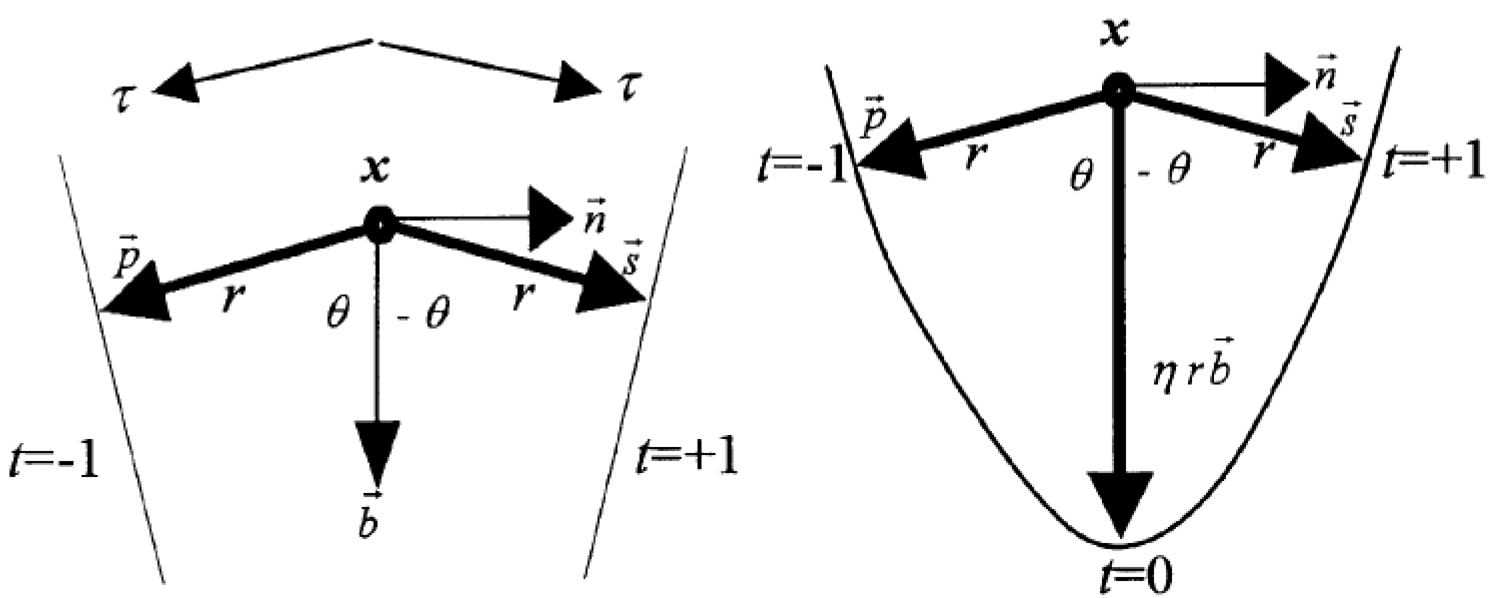


Fig. 4. Medial atom (in bold), its coordinates, and its implied boundary sections. (*left*) An atom internal to the medial locus. (*right*) An atom at endpoints of the medial locus.

I. MEDIAL REPRESENTATIONS

orms of medial locus representations

1) Linked lists of medial atoms that are next to each other to within the resolution of the image data [2], [21] (Fig. 9, left-hand side).
2) Discrete m-reps (*dm-reps*) whose figures are formed as meshes or chains of discrete medial atoms [22] (Fig. 5, top). In dm-reps, end atoms include a third spoke formed in the direction of the bisector between the other two spokes and of length ηr, with $\eta \geq 1$ (Fig. 4) controlling the sharpness of the crest. Attached subfigures in dm-reps ride on the implied boundary of a parent figure.
3) Continuous m-reps (*cm-reps*) whose figures are formed as b-splines of (x, y, z, r) [34] (Fig. 5, bottom). The end curves of these medial manifolds are places that satisfy $|\nabla r| = 1$, where the gradient is taken with respect to Euclidean distance on the medial manifold. At present, these are restricted to single figure objects.

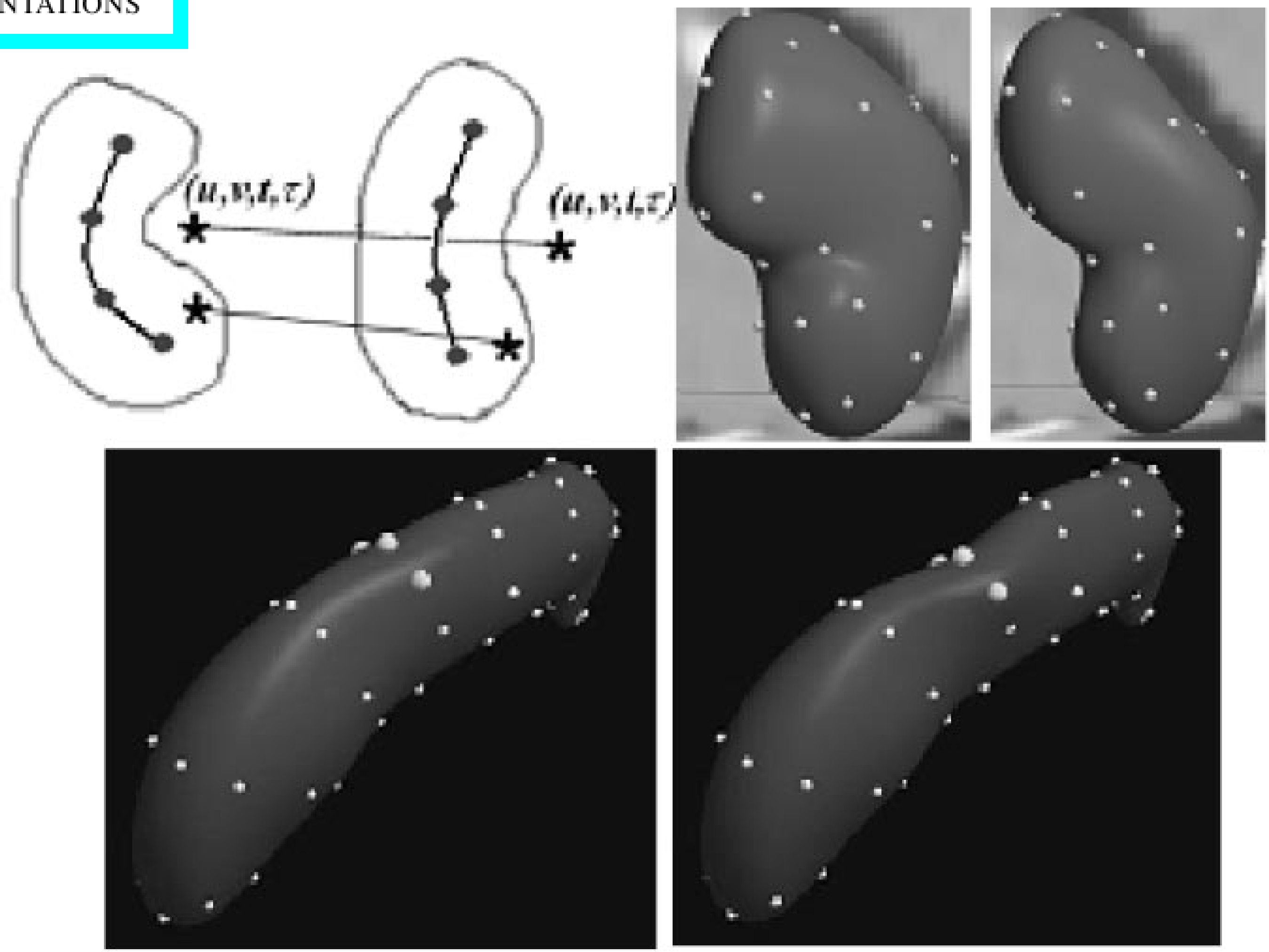


Fig. 7. Positionally corresponding points via figural coordinates. (*top left*) Points in two-space. (*top right*) Boundary points in a deforming kidney. (*bottom*) Boundary points in a statistical principal component analysis medial atom eigenmode on a hippocampus.

II. Medial Representations of Populations of Objects or Object Ensembles

Using the method of Styner, one can take a training sample from a population of objects, each represented as a characteristic image, and produce a common figural topology and dm-rep sampling that can be deformed into any member of the population with a criterion level of accuracy.

They do statistics via Markov random fields by estimating the parameters of the probability distributions of where the first term is measured by .

III. SEGMENTATION VIA MEDIAL REPRESENTATIONS

A. *Segmentation via Deformable m-rep Models*

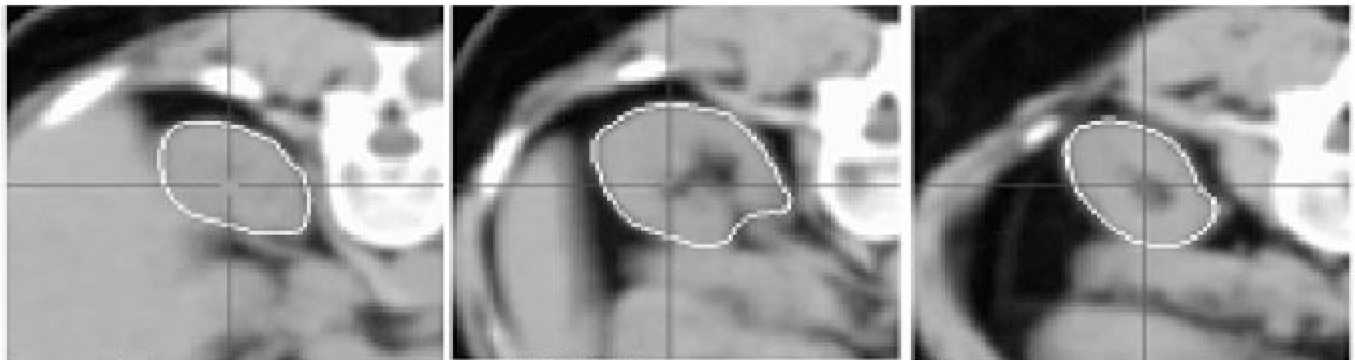
Segmentation of images by deforming an m-rep model, detailed by Joshi *et al.* in [20], is based on a Bayesian framework, scale level by scale level, coarse to fine.

the prior probability density capturing the geometric typicality of the anatomic object residue

and the data likelihood function capturing the image data-to-geometry relationship.

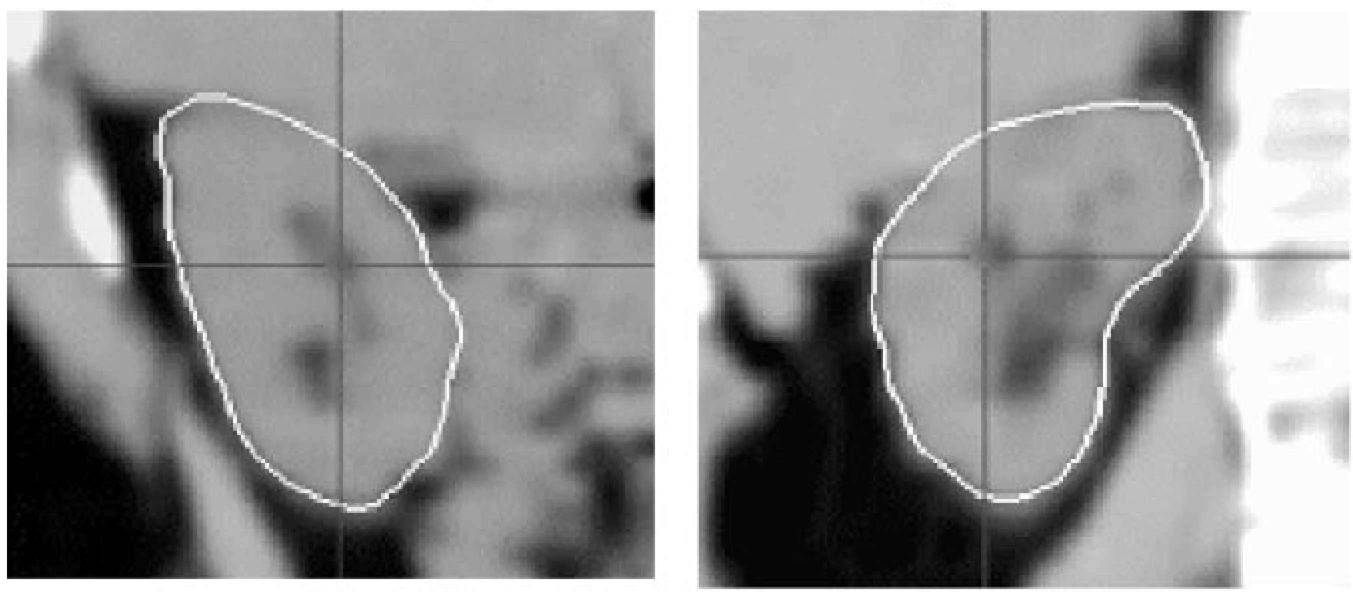
We have been using two basic types of templates: an analytical template computed from derivatives of the Gaussian and an empirical template learned from an example image from which the template medial model was built.

III. Segmentation via Medial Representations



Top Middle Bottom

(see yellow curves above right)



Sagittal Coronal

magnetic resonance angiogram (MRA)

B. *Segmentation via Medial Representations of Tubular Geometry*

Our centerline extraction method operates by an iterative dynamic-scale step-maximize procedure. The eigenvectors of the local scaled Hessian of the image intensity medialness function at one ridge point are used to approximate the tangent and normal directions of the ridge

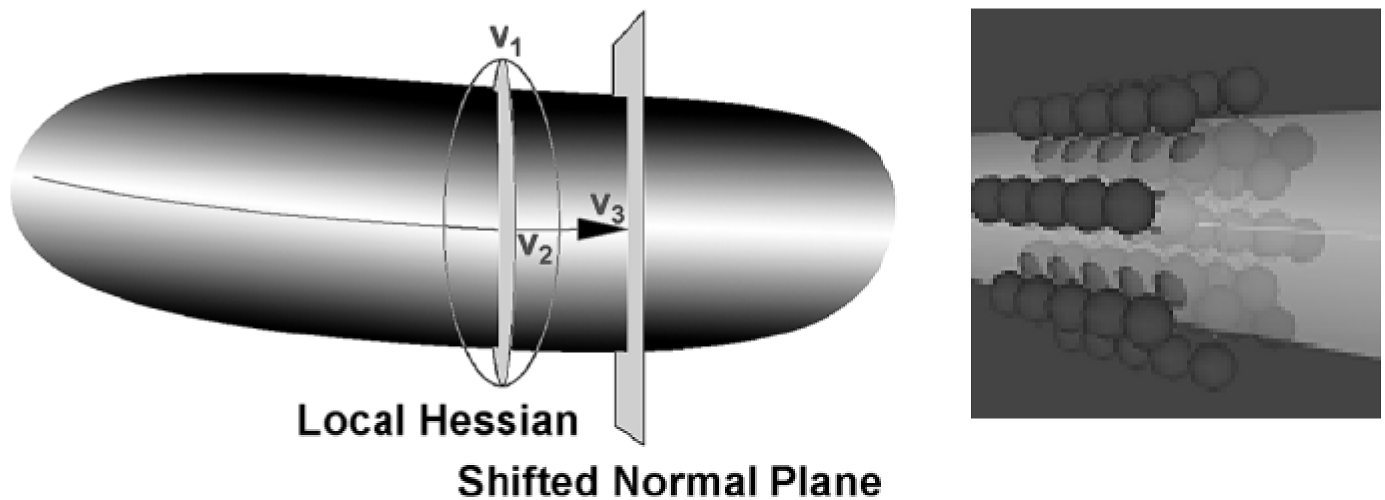


Fig. 9. (*left*) Eigenvectors $(\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3)$ of the local Hessian approximate the tangent $(\mathbf{v}_3)$ and normal $(\mathbf{v}_1, \mathbf{v}_2)$ directions of the ridge. Shifting the normal plane in the tangent direction bounds the search for the next ridge point. (*right*) Series of binary medialness kernels centered on and normal to the ridge are applied at different scales to determine the local radius of the tube.

IV. Registration via Medial Representations of Tubular Objects

. The registration metric measures how well the central axes in a representation map to the ridges in a target image. The orientation and scale of the representations are used to constrain a coarse-to-fine registration optimization process such that a vessel curve segment whose medial tangent vector is $\vec{b}$ is only used to resolve alignment orthogonal to $\vec{b}$. The sparseness of the representations also speeds the registration process

Usan RMF

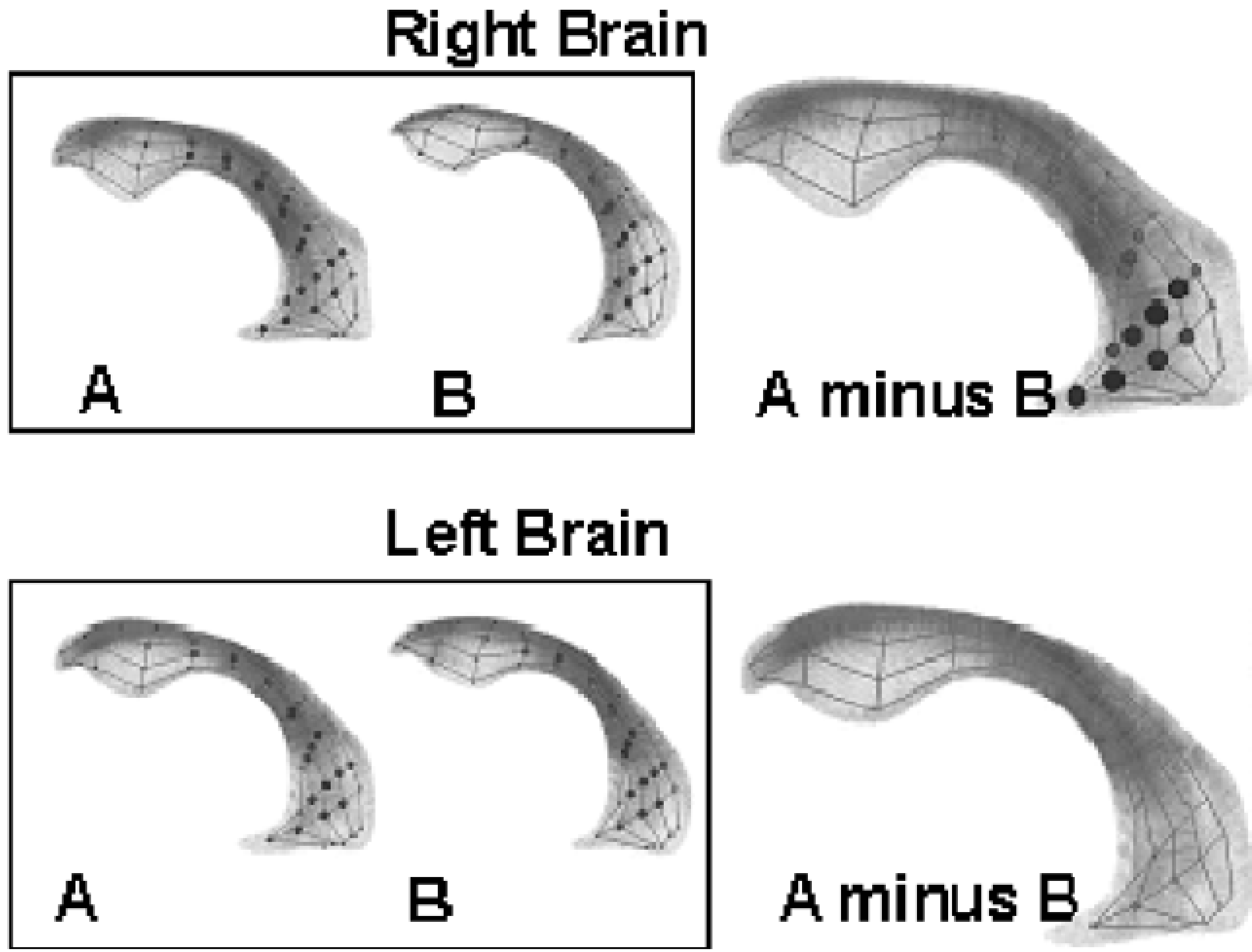


Fig. 11. Shape comparison of ventricles based on medial representations. The larger figures represent the medial mesh with width (radius) difference at corresponding mesh points. The size of the disks indicate local differences between twins A and B in the range of −0.3–1.5 mm.

VI. Conclusion

- La representación se compone de átomos
- Utilizan mallas
- Utilizan Dm-rep para multiescala (enssembles)
- Utilizan un marco bayesiano
- Utilizan RMF