Poincaré sphere representation of independent scattering sources: Application on distributed targets

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The principal idea:

Eigenvalue decomposition

$\Longleftrightarrow$

Principal Component Analysis (PCA) → Statistically **Uncorrelated** sources

Independent Component Analysis (ICA) → Statistically **Independent** sources

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Target Scattering Vector Model (TSVM)

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Application on snow cover

- ❑ The principal idea
- ❑ Blind Source Separation
- ❑ Method description
- ❑ TSVM and Poincaré sphere representation
- ❑ Application on snow cover
- ❑ Conclusions & Further work

$$\underbrace{\begin{bmatrix} x_1(i,j) \\ x_2(i,j) \\ x_3(i,j) \end{bmatrix}}_{\text{Observations Vector } \boldsymbol{X}} = \underbrace{\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}}_{\text{Mixing Matrix } \boldsymbol{A}} \cdot \underbrace{\begin{bmatrix} s_1(i,j) \\ s_2(i,j) \\ s_3(i,j) \end{bmatrix}}_{\text{Sources Vector } \boldsymbol{S}}$$

Principal Component Analysis (PCA):

- Matrix ***A*** estimation limited to the second order statistics;
- The obtained sources ***S*** are mutually uncorrelated;

Mixing matrix having un-normalized eigenvectors of the observation vector covariance matrix as columns, ensures decorrelation between the sources.

Independent Component Analysis (ICA):

- Matrix ***A*** estimation using higher order statistics;
- Ensuring independence by maximizing Non-Gaussianity of the sources;

- Several different criteria:

  - **Maximizing kurtosis:**

$$kurt(s_i) = E\{s_i^4\} - 3\left(E\{s_i^2\}\right)^2$$

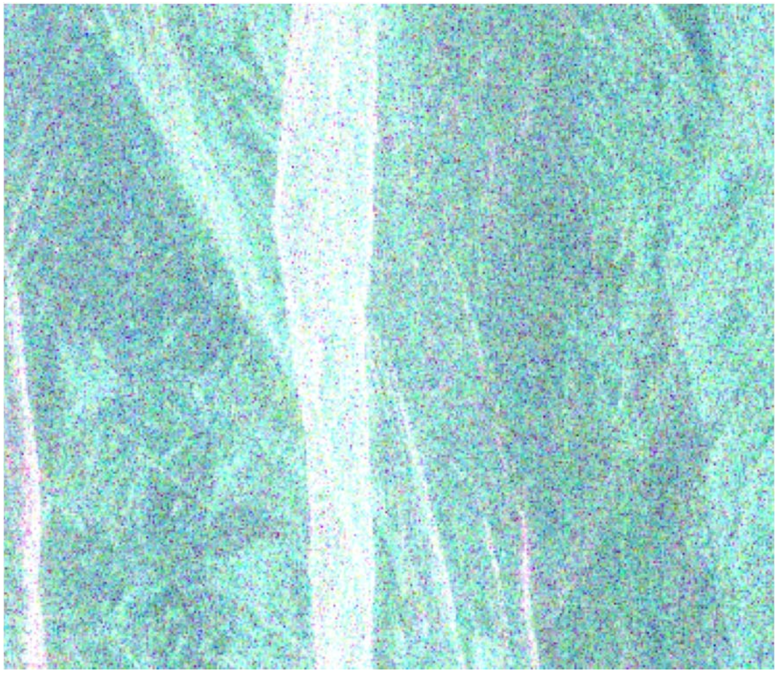
  - Maximizing negentropy:

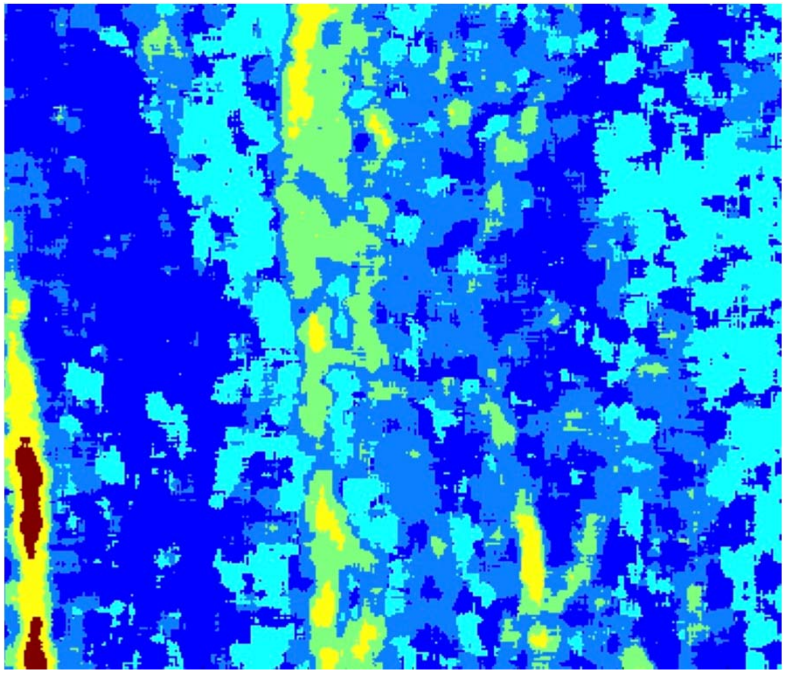
$$H(s_i) = H(s_{gaussian}) - H(s_i)$$

  - Minimizing Mutual Information,
  - **Maximum Likelihood Estimation.**

Step I:

- **Statistical classification (global approach)**





  - Initialization in the form of H/ alpha unsupervised classification;
  - Classes barycenters computation based on distance in covariance space;
  - Wishart criterion in pixels assignment;

  P. Formont, et al., "H/α Unsupervised Classification for highly textured Polinsar Images using Information Geometry of Covariance Matrices", POLinSAR 2011.

- **Sliding window (local approach)**

Step II: Applying ICA (*FastICA algorithm*) to each of the classes / windows

Mixing matrix
***A*ᶜ**

$$\underbrace{\begin{bmatrix} S_{HH}(i,j)+S_{VV}(i,j) \\ S_{HH}(i,j)-S_{VV}(i,j) \\ 2S_{HV}(i,j) \end{bmatrix}}_{\text{Target vectors belonging to class } c} = \underbrace{\begin{bmatrix} a_{11}^{c} & a_{12}^{c} & a_{13}^{c} \\ a_{21}^{c} & a_{22}^{c} & a_{23}^{c} \\ a_{31}^{c} & a_{32}^{c} & a_{33}^{c} \end{bmatrix}}_{\text{Independent target vectors}} \cdot \underbrace{\begin{bmatrix} s_1(i,j) \\ s_2(i,j) \\ s_3(i,j) \end{bmatrix}}_{\text{Sources Vector}}$$

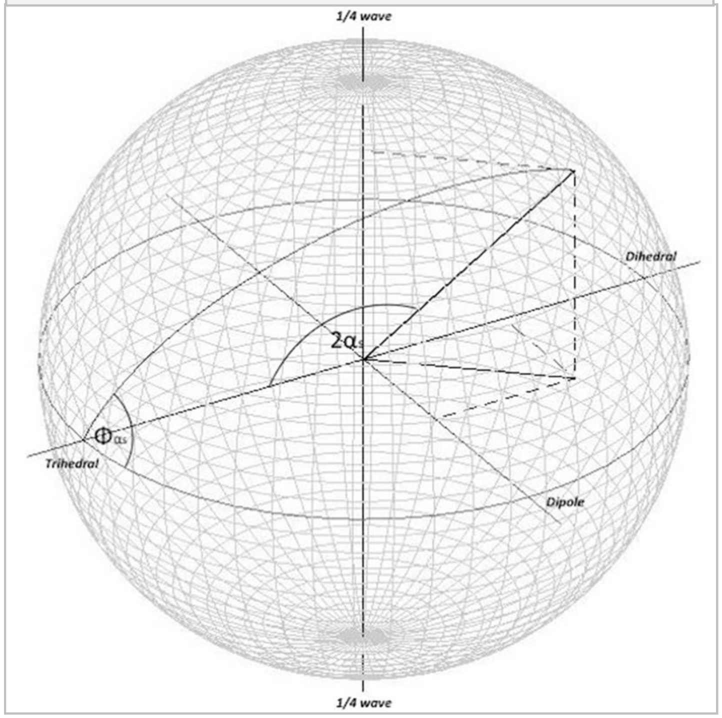
- *Sources energies fixed: unity variances.*
- *Contribution of the independent backscattering mechanism:* ***squared norm of the corresponding column of A^c****.*

Step III: Parameterization

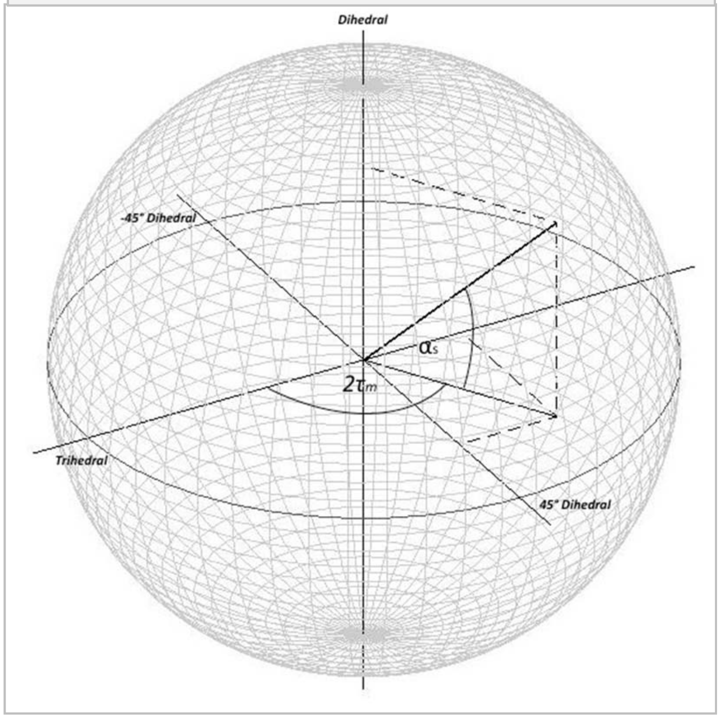
$$\begin{bmatrix} a_{1i}^{c} \\ a_{2i}^{c} \\ a_{3i}^{c} \end{bmatrix} = m_i^c \left|a_i^c\right|_{m_i^c} e^{j\Phi_{s_i}^c} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\left(2\psi_i^c\right) & -\sin\left(2\psi_i^c\right) \\ 0 & \sin\left(2\psi_i^c\right) & \cos\left(2\psi_i^c\right) \end{bmatrix} \begin{bmatrix} \cos\alpha_{s_i}^c \cos\left(2\tau_{m_i}^c\right) \\ \sin\alpha_{s_i}^c e^{j\Phi_{\alpha_{s_i}}^c} \\ -j\cos\alpha_{s_i}^c \sin\left(2\tau_{m_i}^c\right) \end{bmatrix}$$

Target Scattering Vector Model (TSVM) [Touzi]

symmetric targets



non-symmetric targets



Algorithm applied on two ALOS POLSAR images of snow covered area.
(L band, quad-pol, Chamonix - Mont Blanc, France, 2008-02-26)

•Extracted helicity parameter of the most dominant independent component:

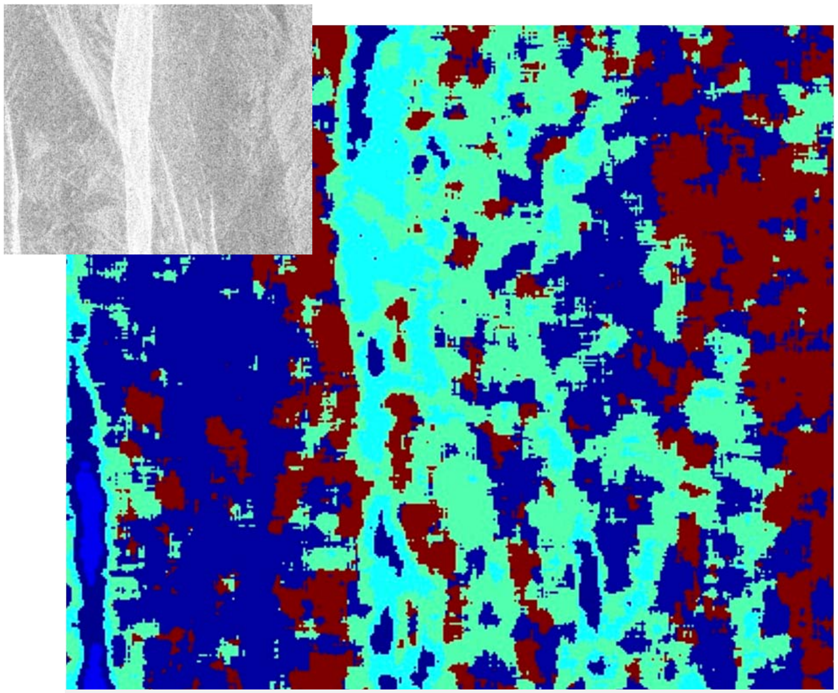


Image I: 8 classes

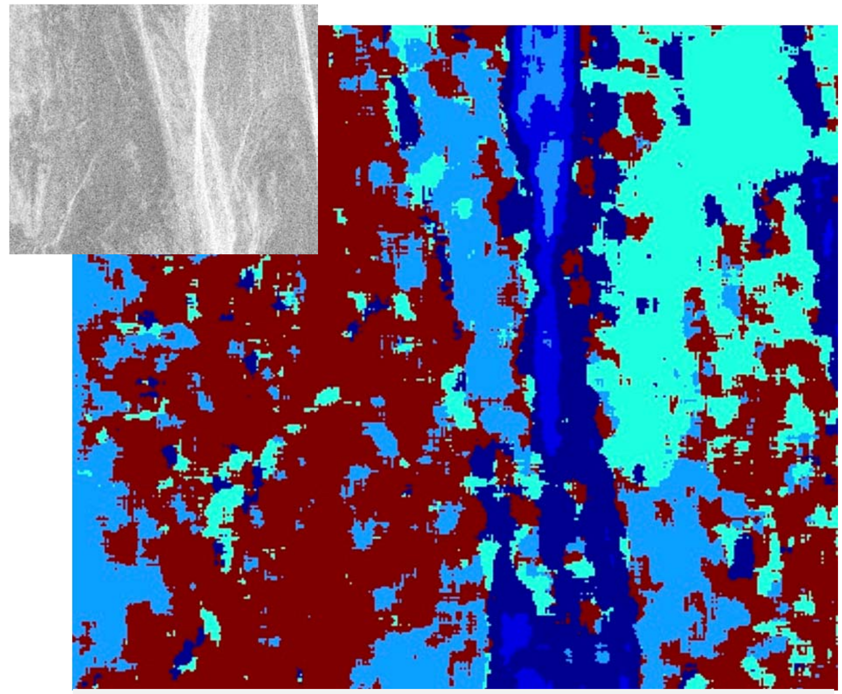


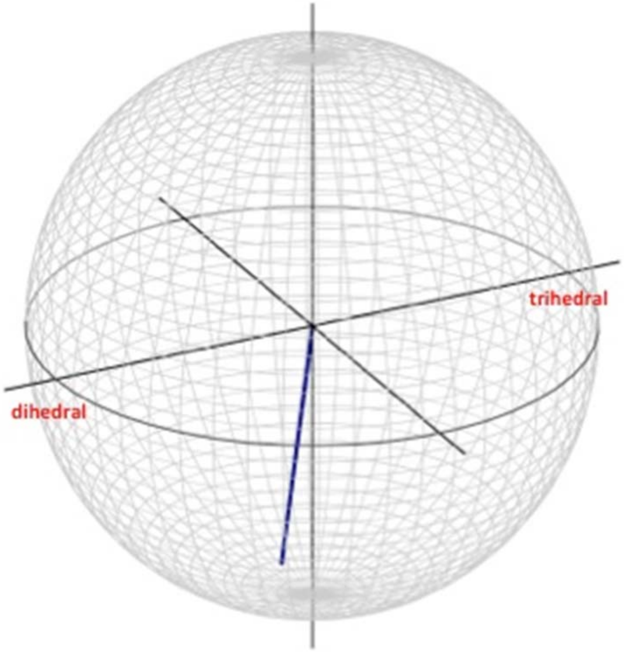
Image II: 8 classes

Image I	Image II	Image II
-5.2656˚	5.9644˚	3.2994˚

- **Non-symmetric targets: bare ground and dry snow regions**
- **Symmetric targets: wet snow regions**

Algorithm applied on two POLSAR images of snow covered area.

•Poincaré sphere representation of the dominant symmetric components:



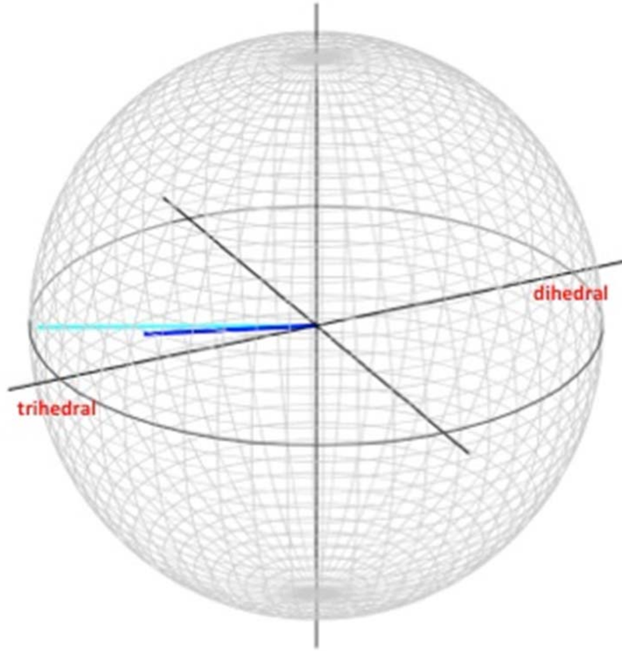


	Image I	Image II	Image II
α_s	-59.27°	14.81°	-7.34°
Φ_{α_s}	35.41°	37.10°	-21.22°

No matching in case of global approach (statistical classification)

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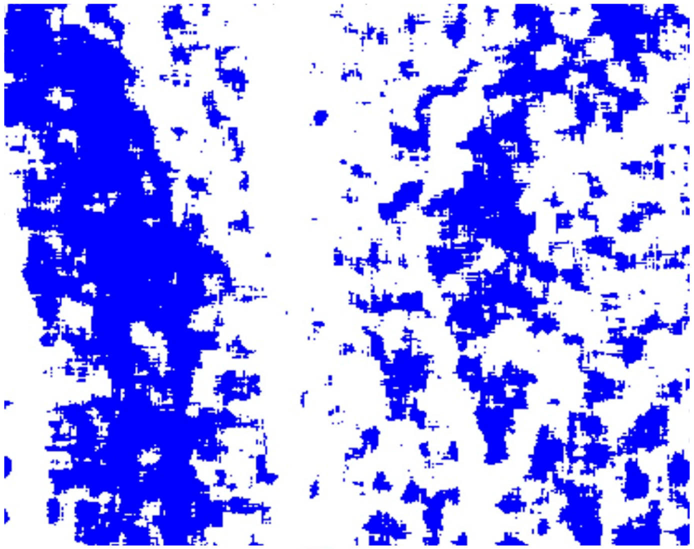
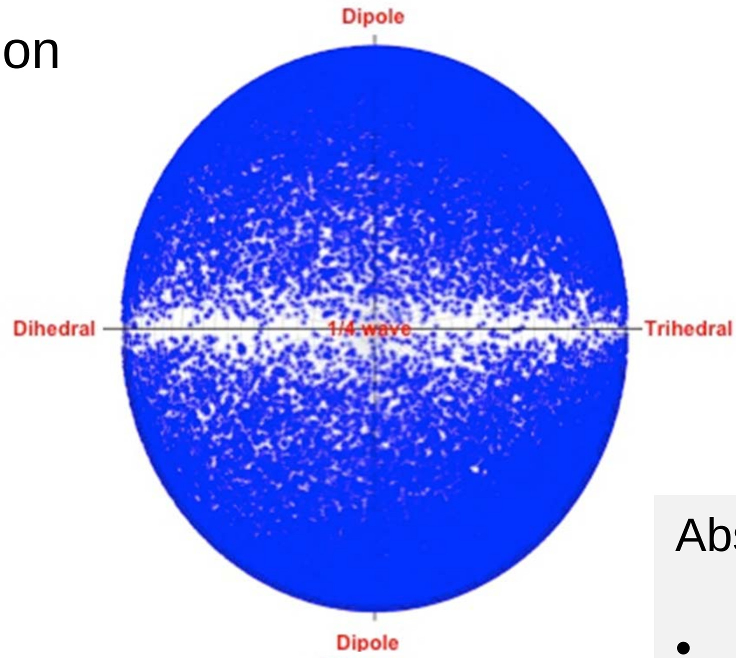
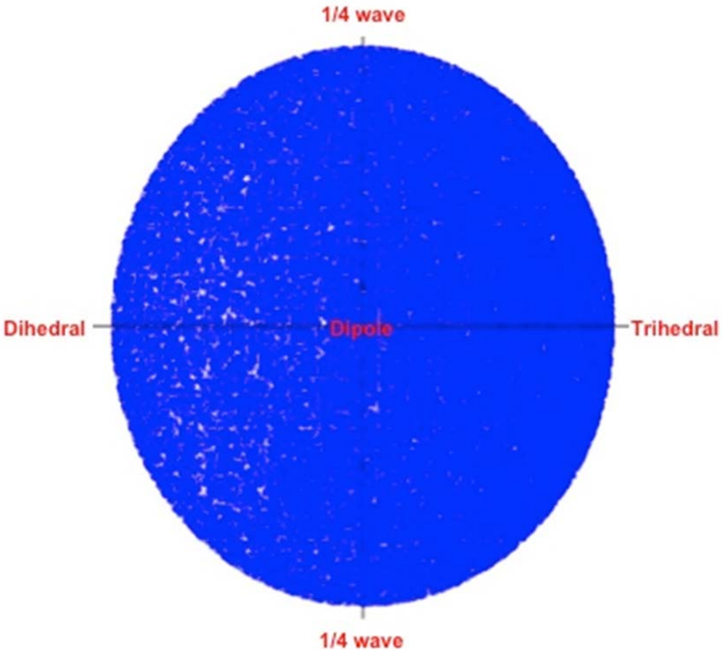
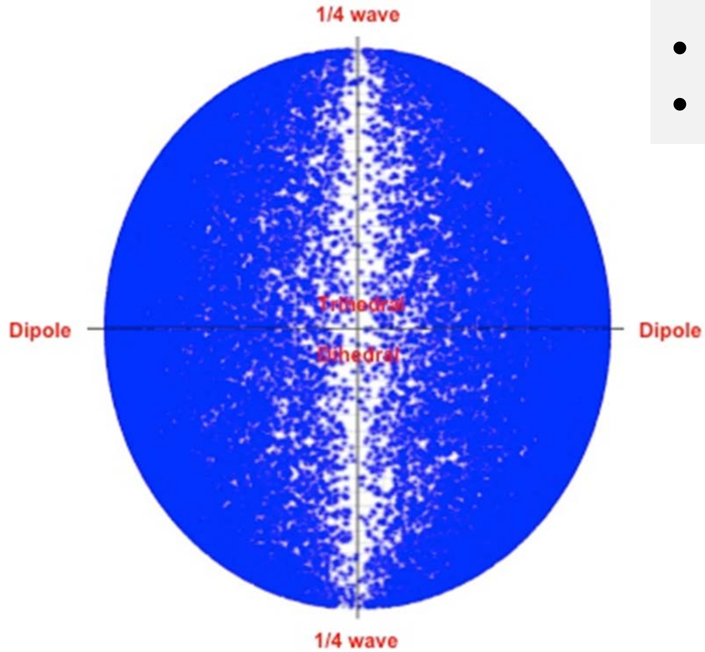
Local approach within the predefined classes

Image I, Class I: Wet snow region





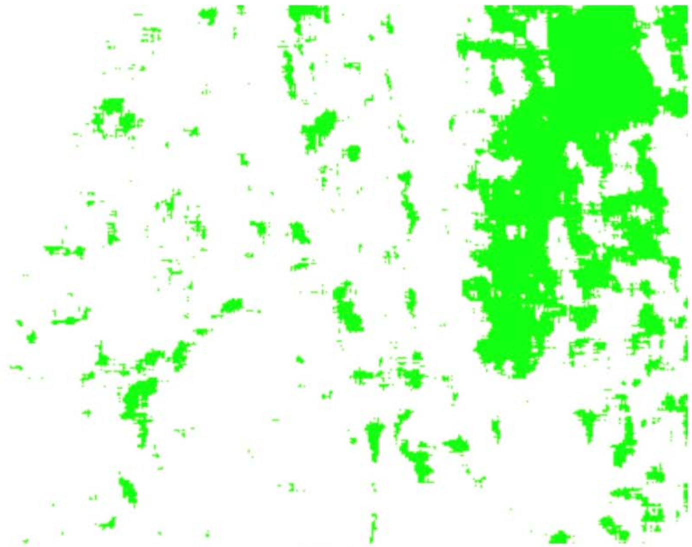


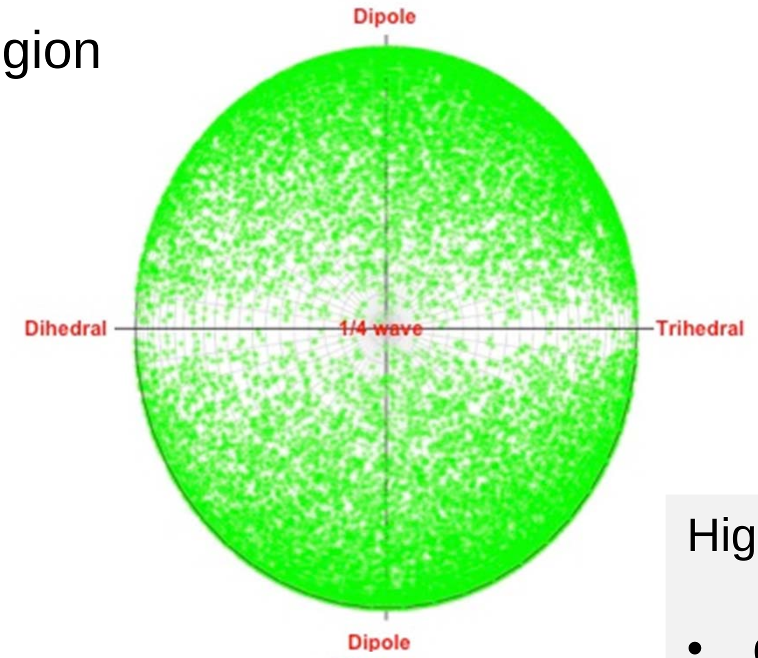


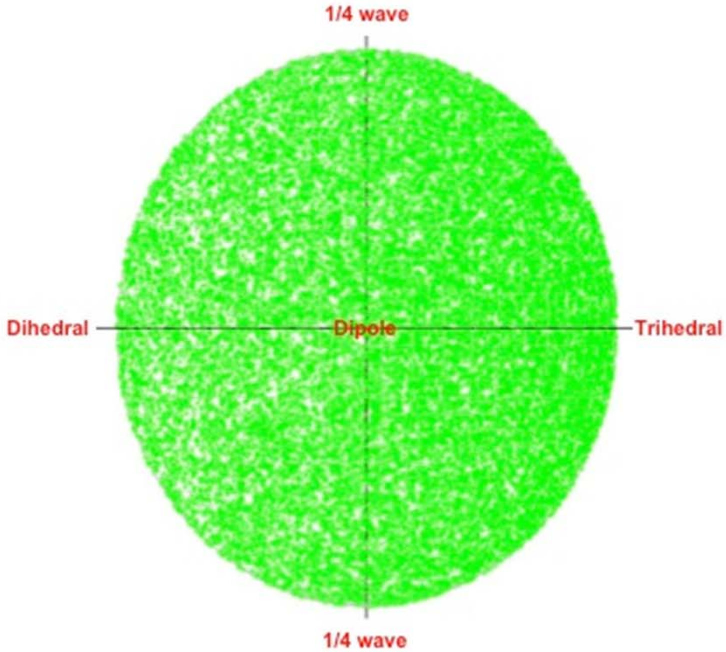
Absence of:

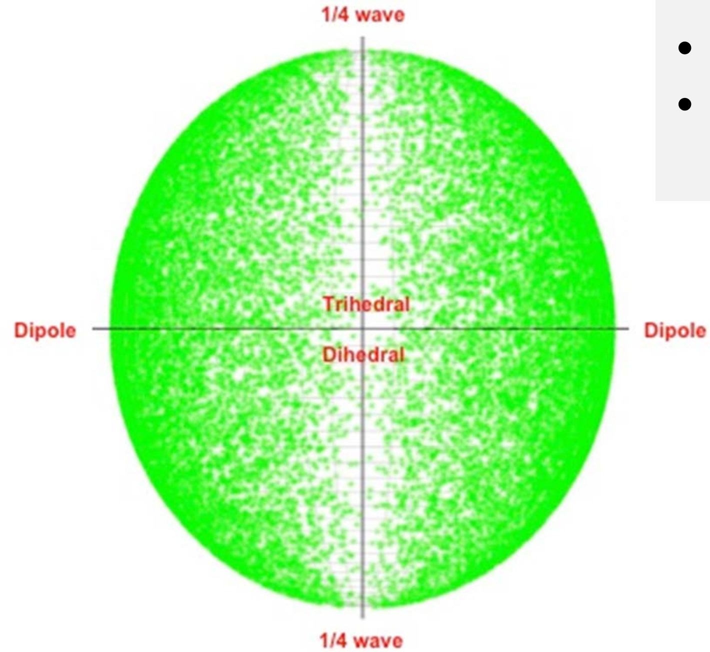
- symmetric trihedrals
- symmetric dihedrals
- 1/4 wave scatterers

Image II, Class II: Wet snow region





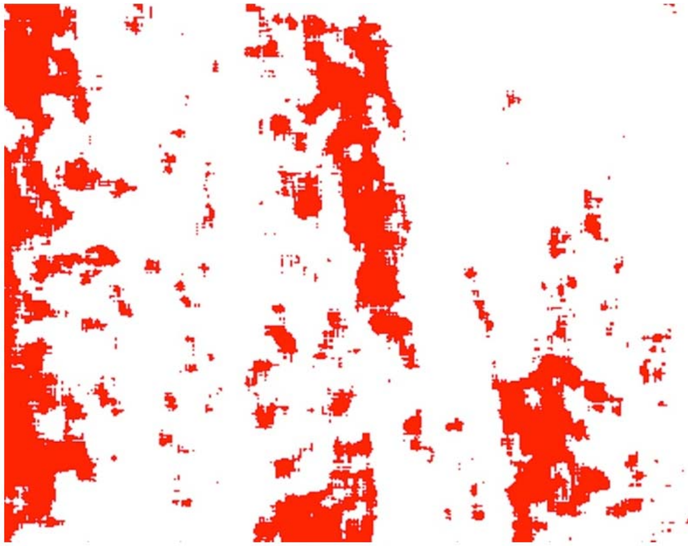


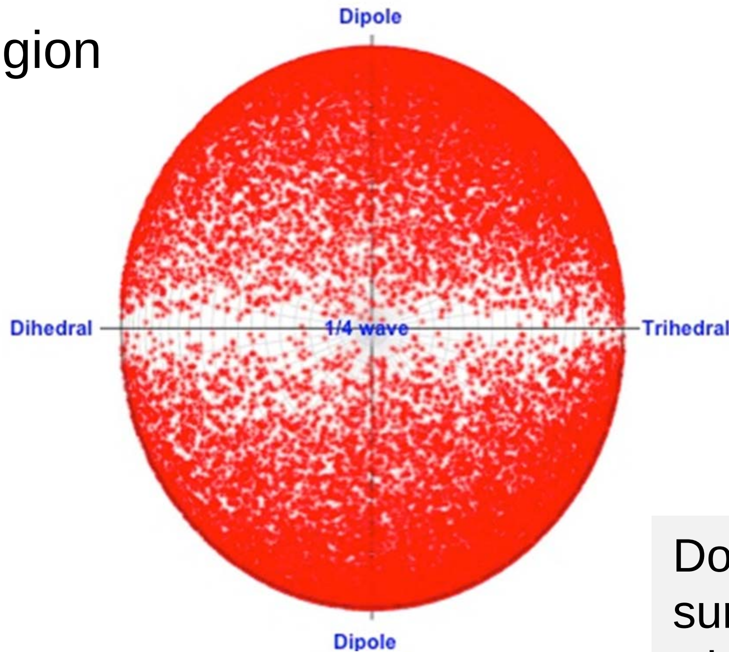


High concentration of:

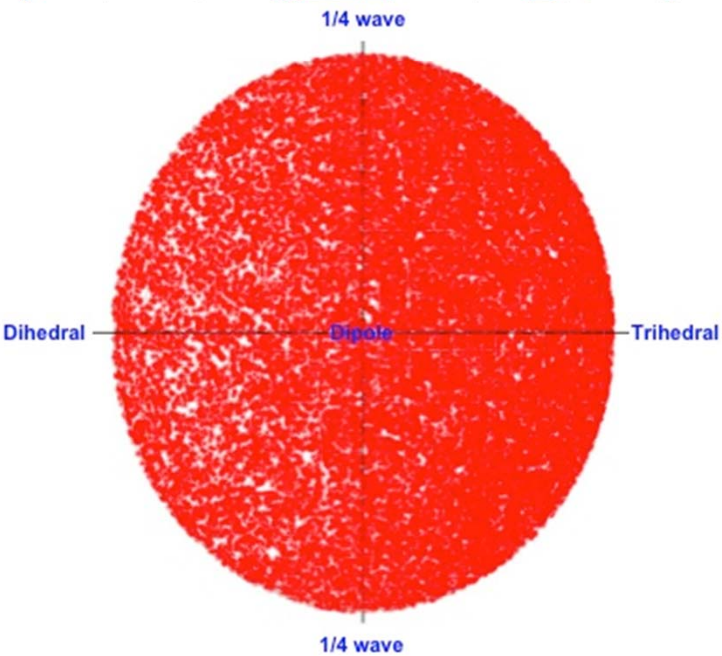
- dipoles
- symmetric cylinders
- symmetric narrow dihedrals

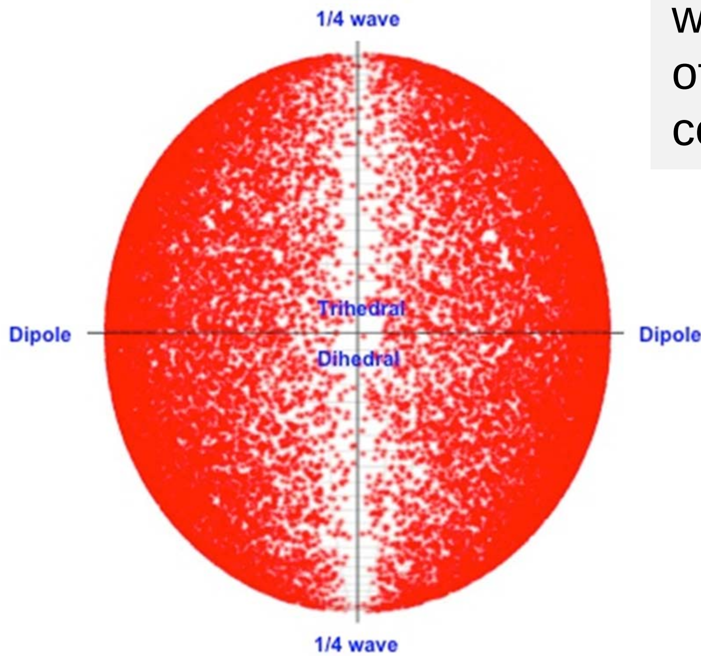
Image II, Class III: Wet snow region





Dominance of snow surface backscattering, with certain contribution of volume backscattering component.





Conclusions & Further work:

Conclusions:

- Possibility of recovering independent (non-orthogonal) backscattering mechanisms.
- Discrimination between wet snow on the one side and the dry snow and bare ground on the other side using helicity parameter of the most dominant independent scatterer.
- Dominance of dipole elementary scatterers in case of a wet snow.

Further work:

- Roll-invariance analysis of the maximum amplitude parameter.
- Comparison between different ICA criteria in the context of polarimetric decomposition.
- Physical interpretation of the obtained results in case of snow as a target.

Thank you

for

your attention!