Automatic Detection and Classification of Sunspot Images

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Joint work with Vinay Kashyap, David Stenning, David van Dyk and Alex Young

Outline

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1. Background and Goal

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   (a) Detection

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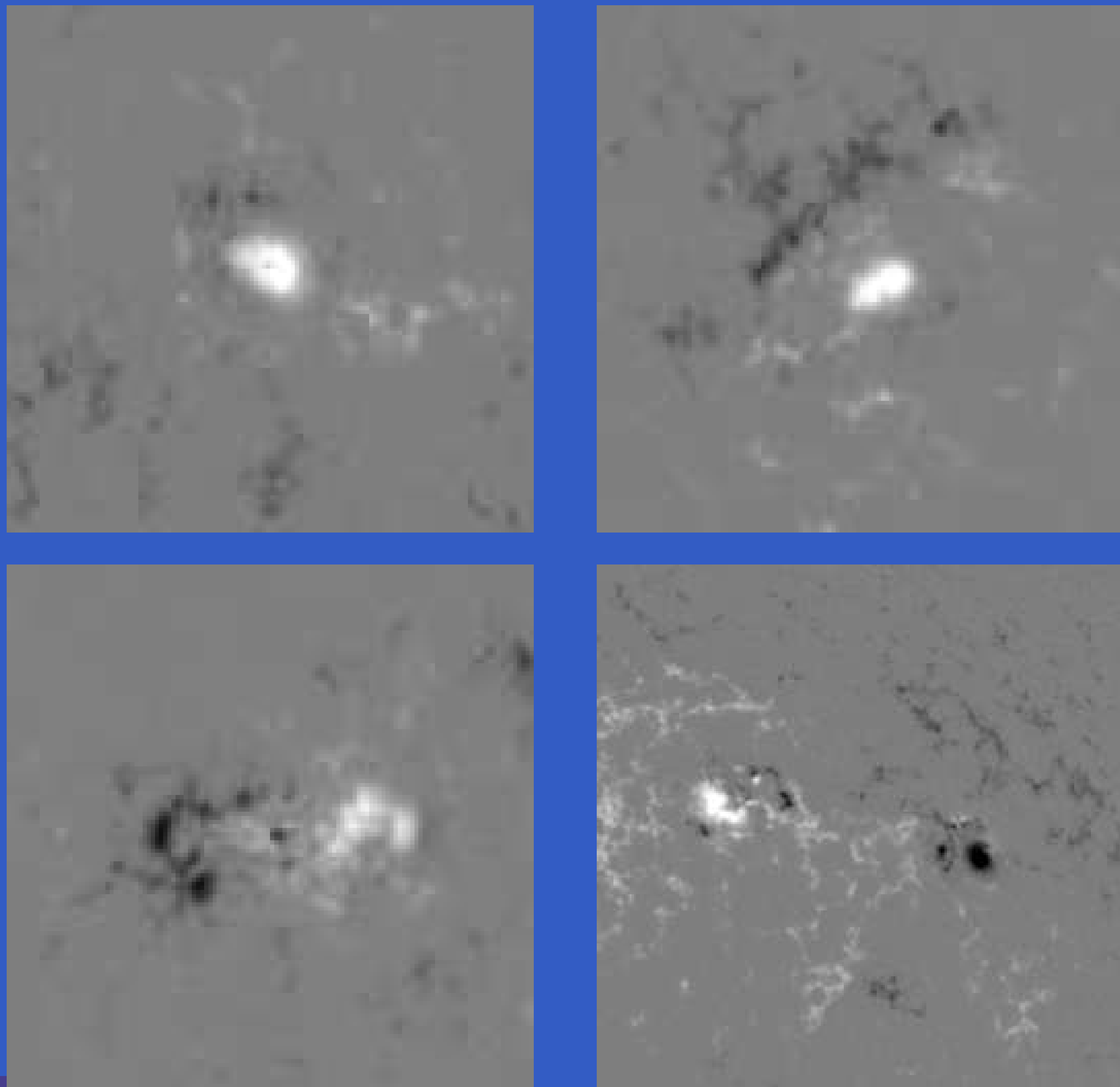
- magnetograms: images represent variations in the strength of magnetic fields in the sun’s photosphere
- sunspots can also be seen in magnetograms
- as bright or dark areas, representing opposite polarities

Some Magnetograms with Sunspots



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- still on-going work

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- even for the simple Mount Wilson rules, trained experts do not always agree on classifications
- also huge volume of data (Solar Dynamics Observatory: data downlink rate of 130 megabits/s)
- therefore we need an automated, objective and reliable procedure for sunspot detection and classification

Mount Wilson Classification Scheme

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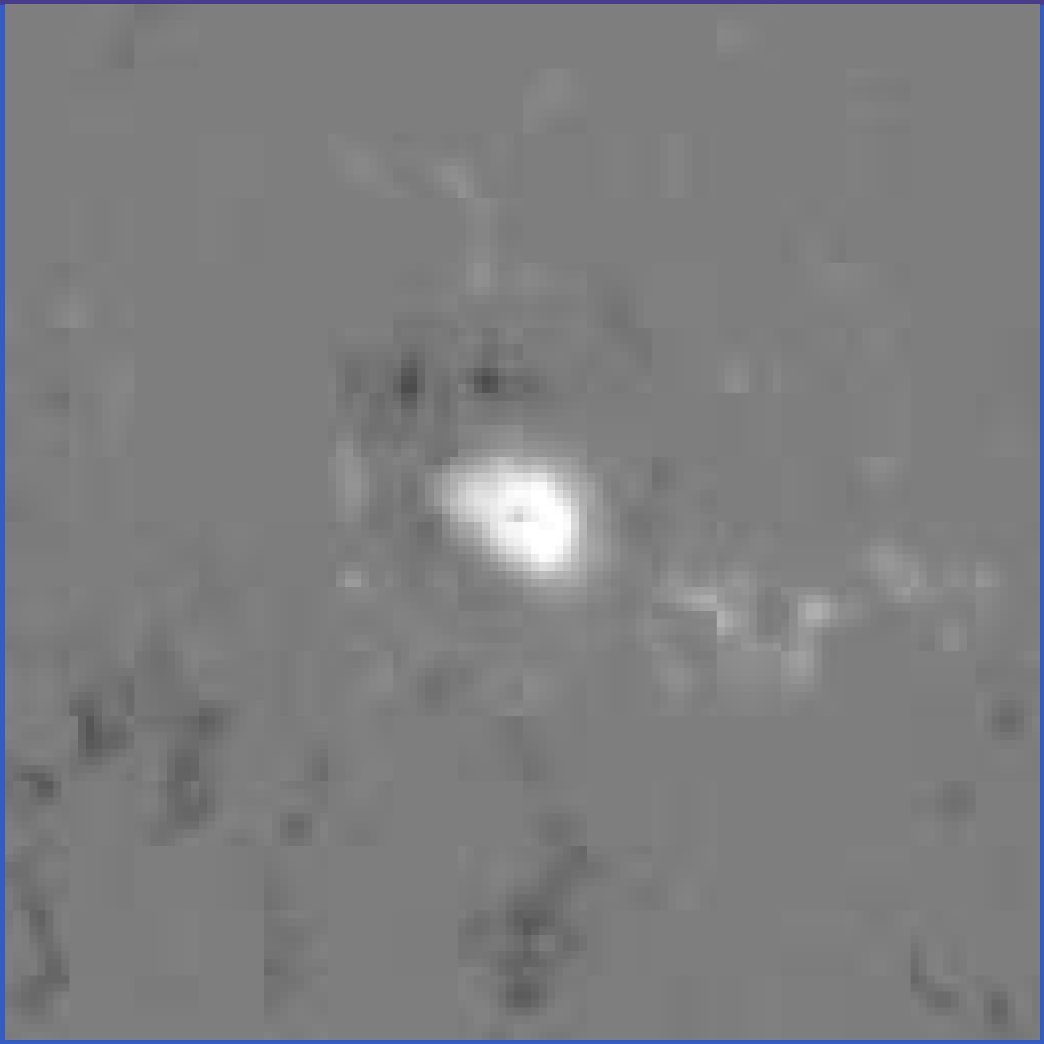

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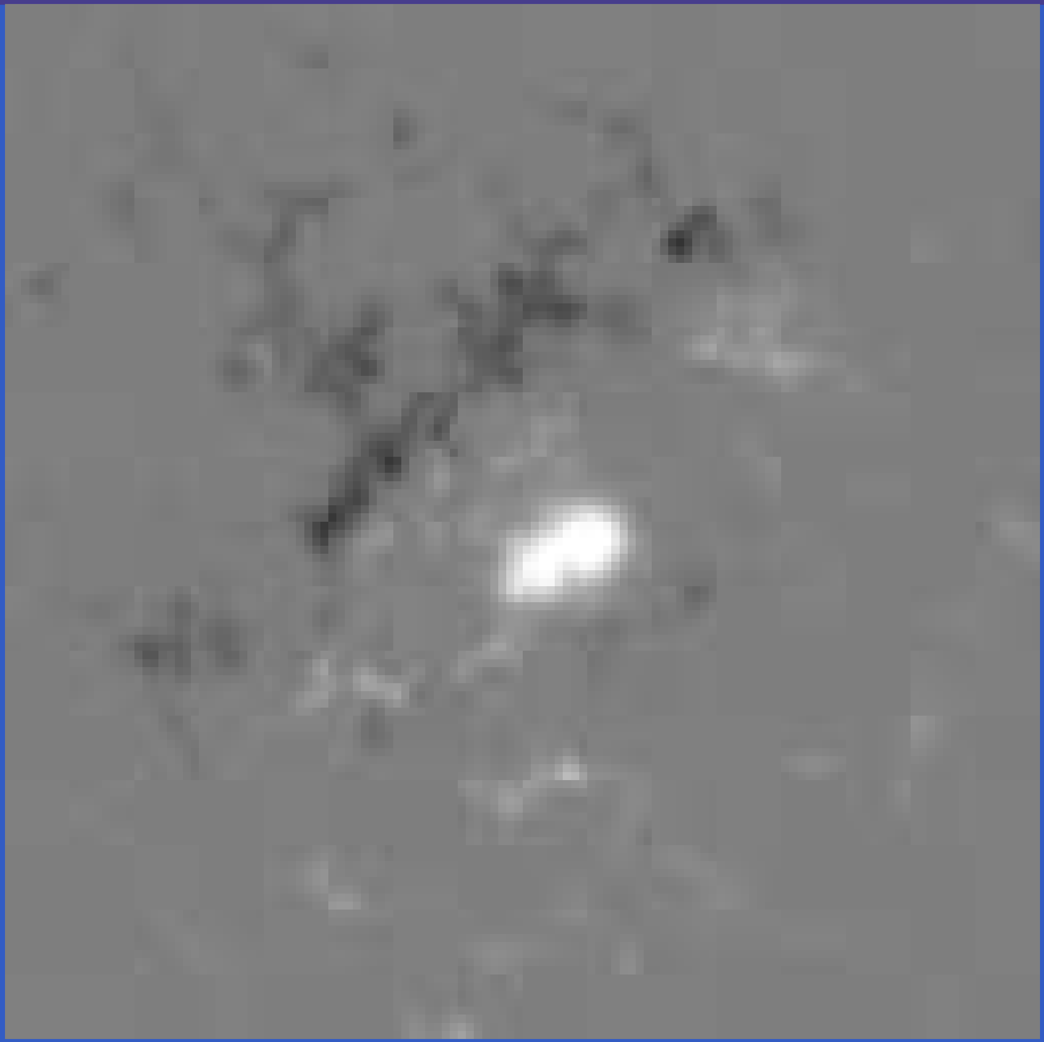

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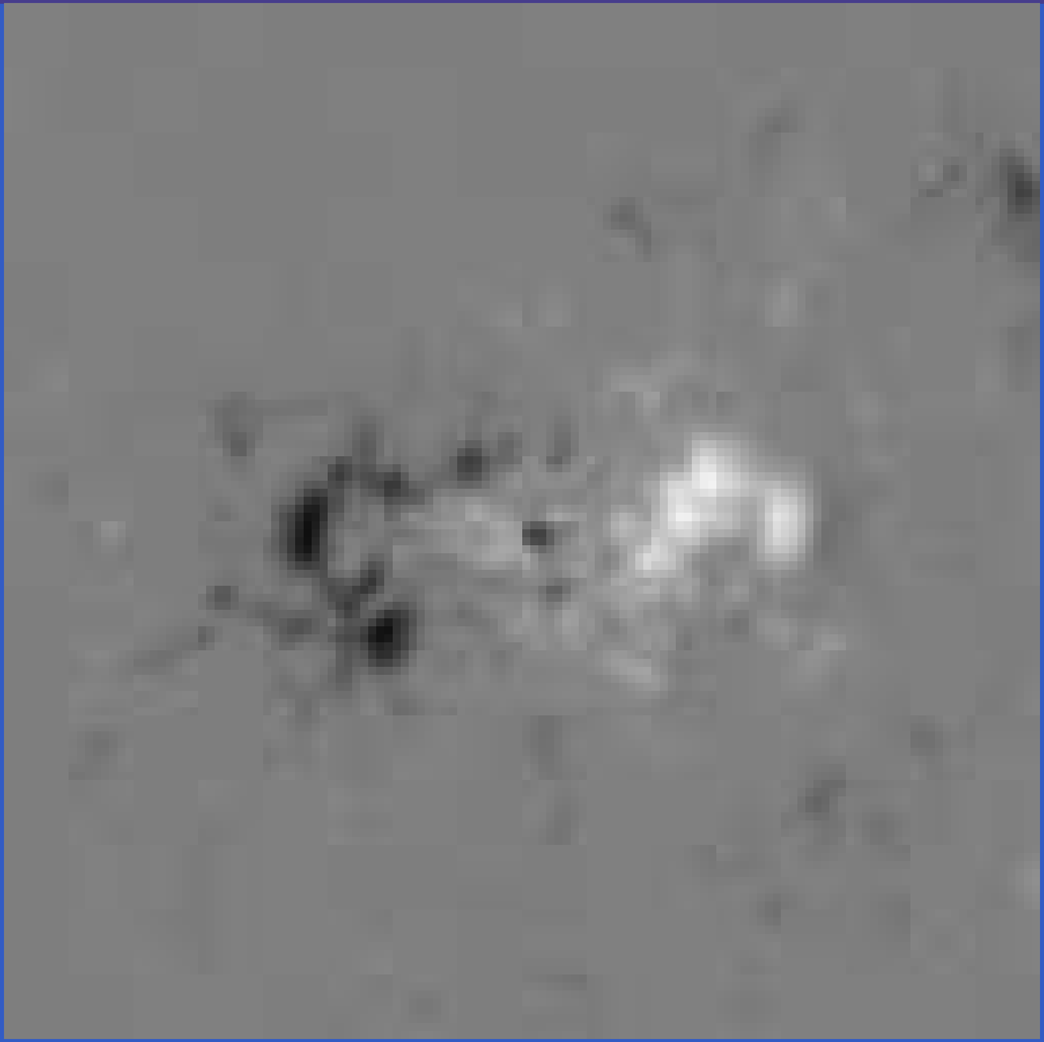

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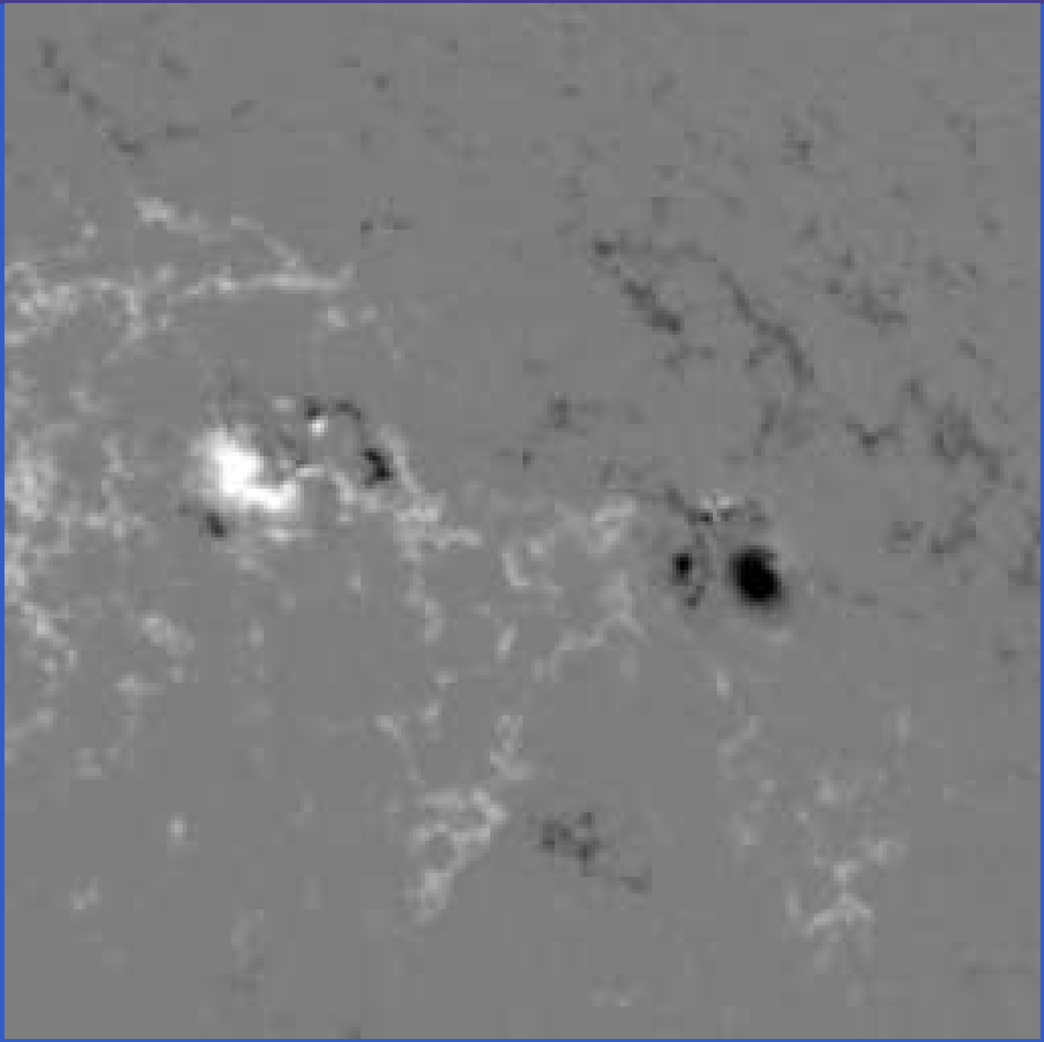
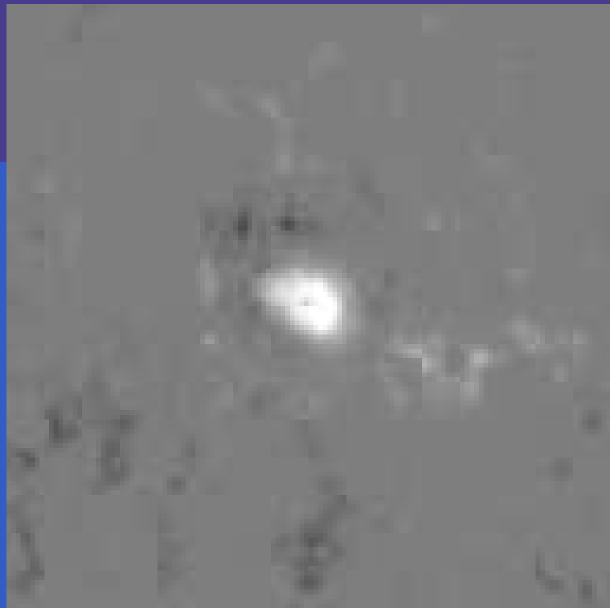
  4. beta-gamma-delta: bipolar, with positive and negative polarities scatter throughout the region and cannot be easily separated

beta-gamma-delta



alpha



beta

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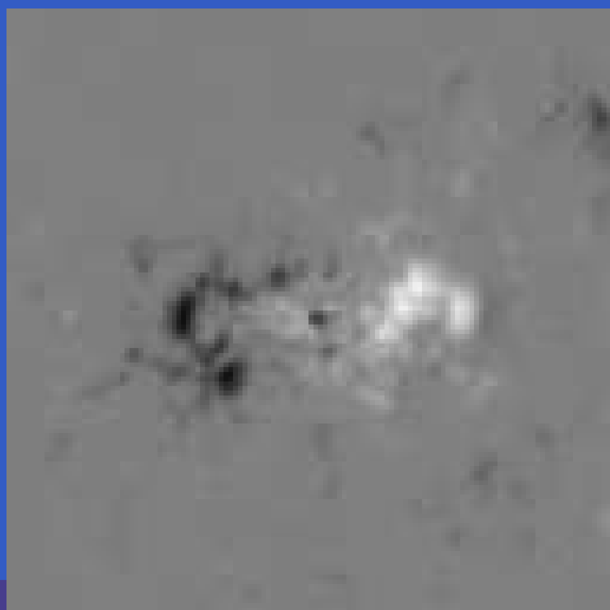
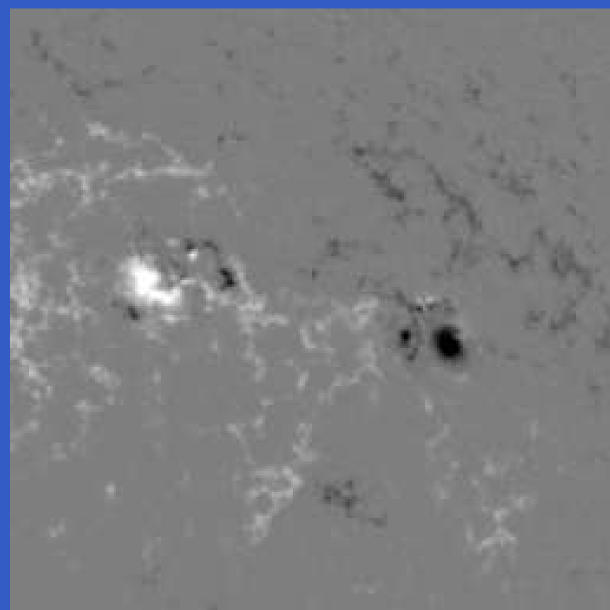


beta-gamma-delta



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- we are in between

Sunspot Detection

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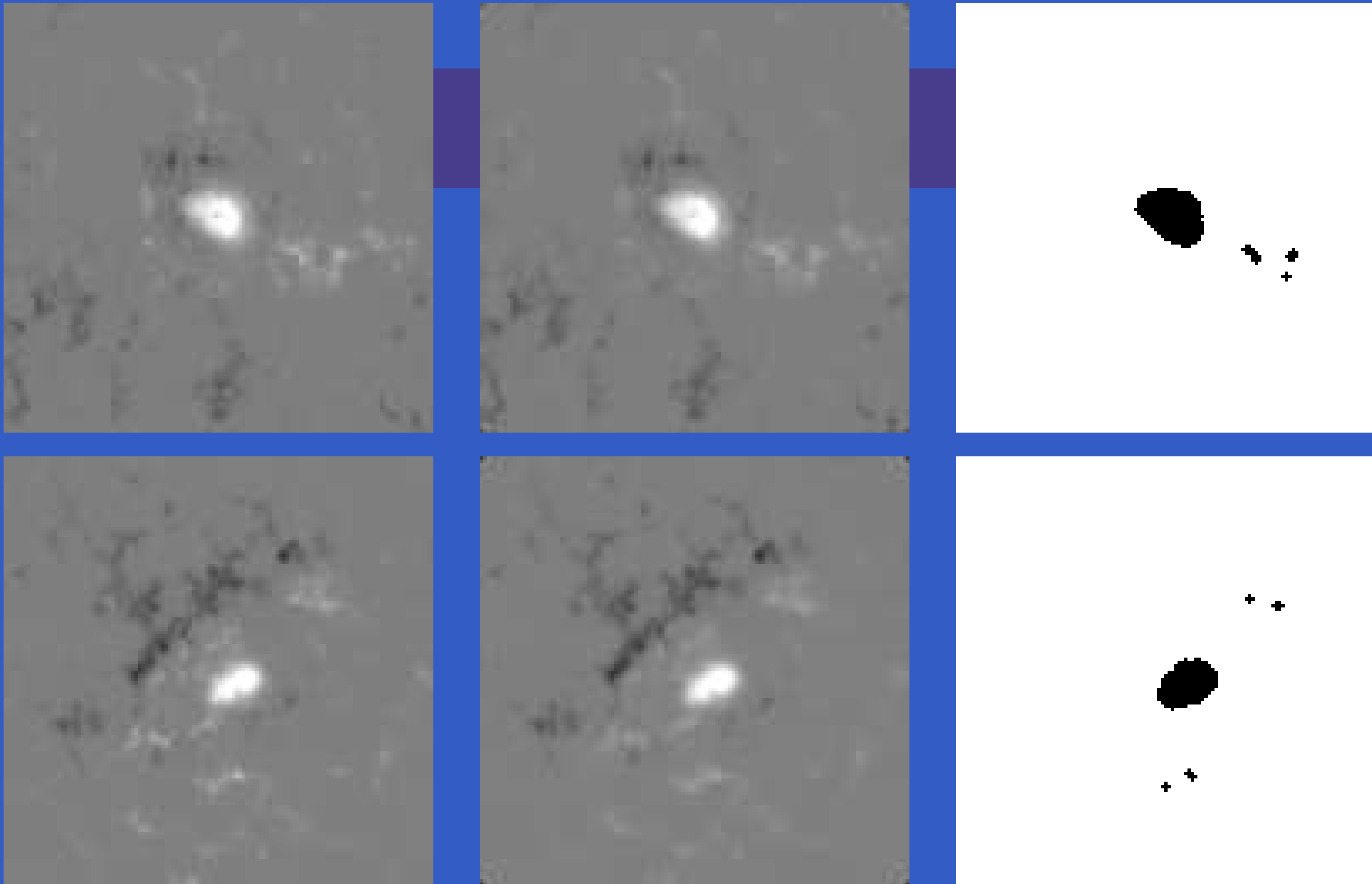
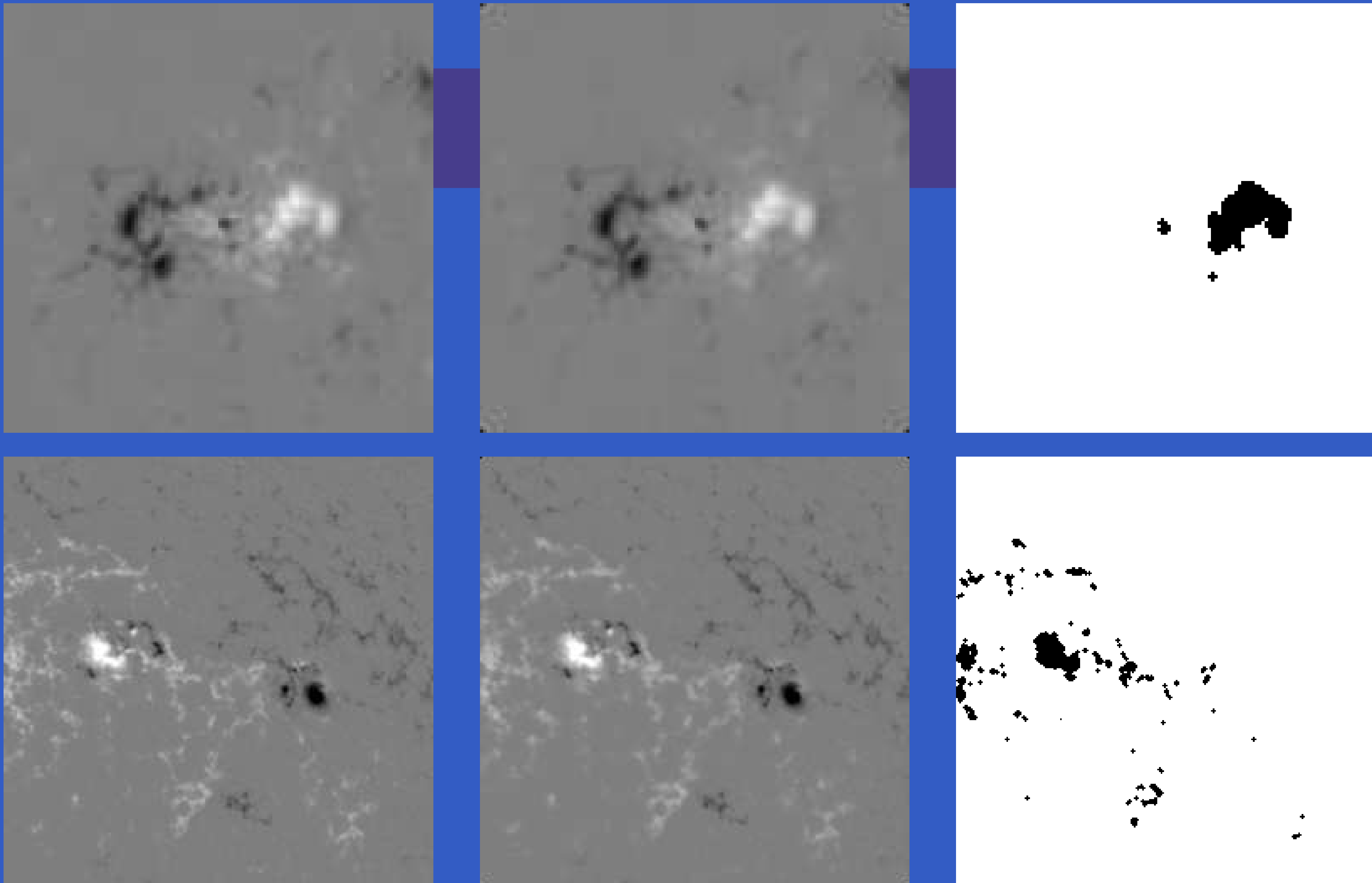
- black sunspots: apply the same steps to the negative of the image



original cleaned thresholded



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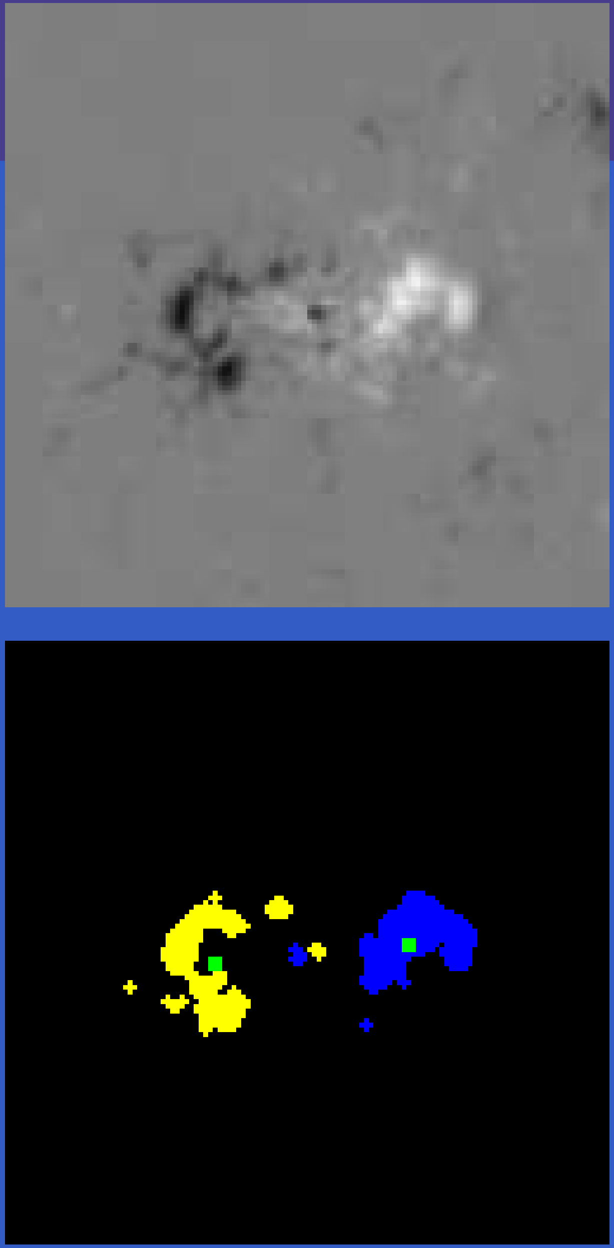
- we propose a new measure for feature 3

beta-gamma



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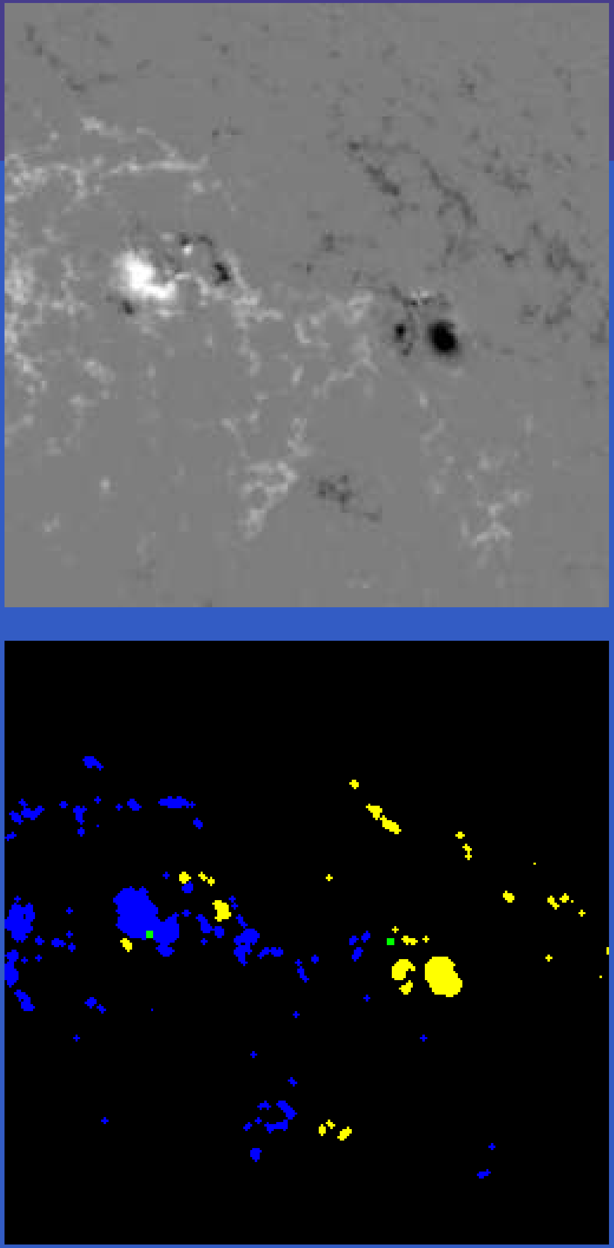

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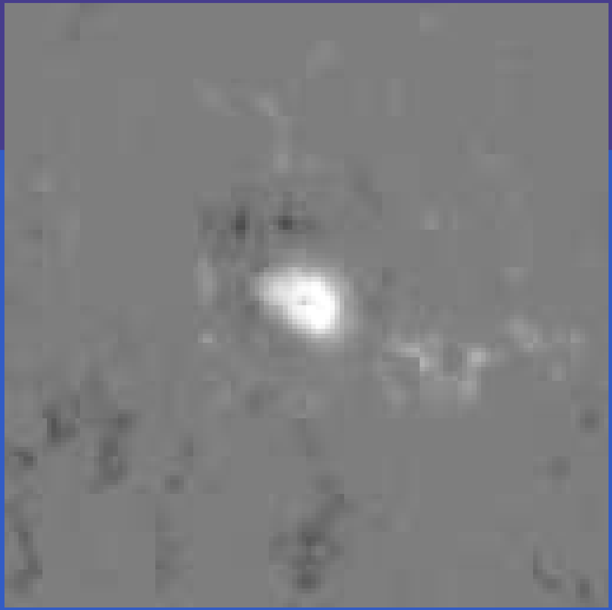
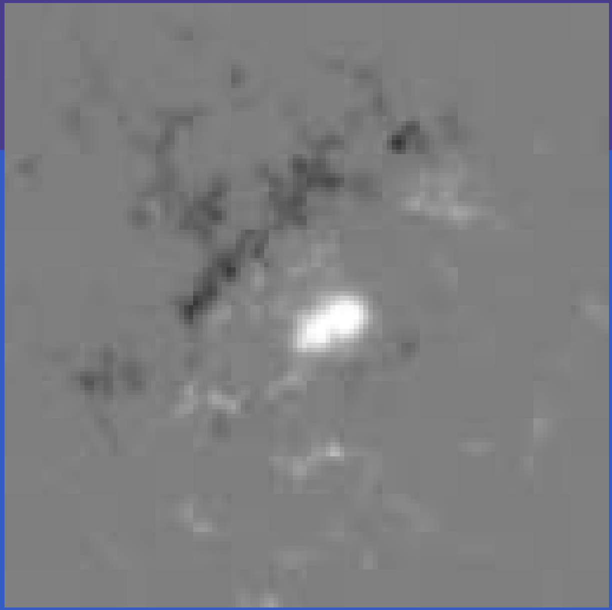
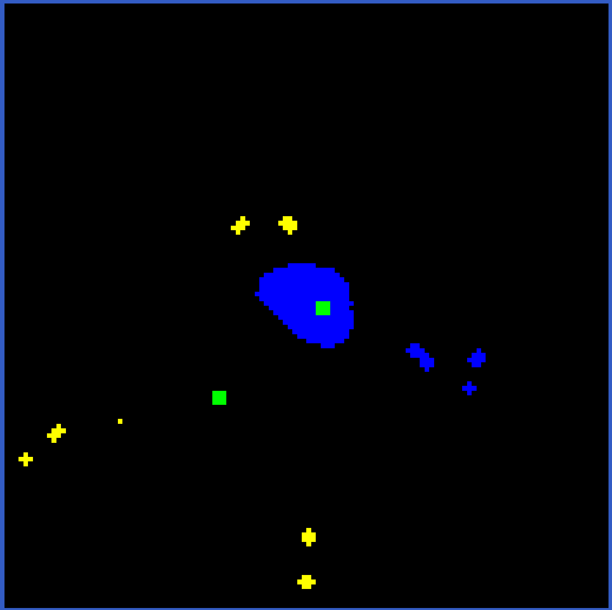
- similarly for black sunspot pixels: $A(B)$

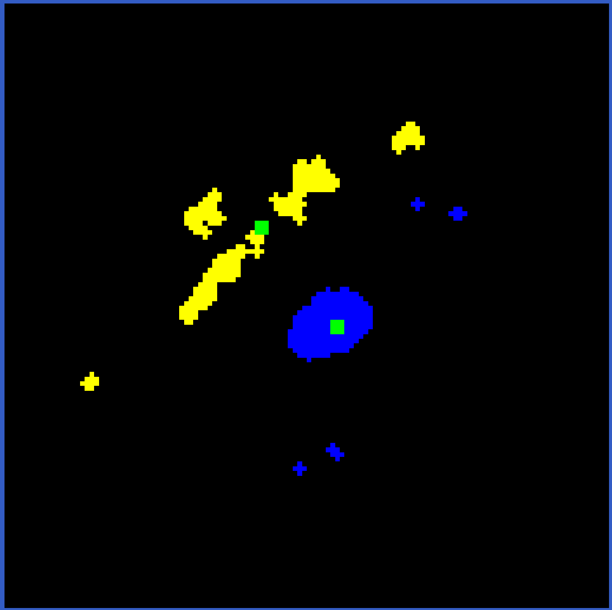
alpha | beta





$$\left(\frac{|W|}{|B|}, A(W), A(B)\right)$$





(6.13, 0.07, 0.95) | (0.78, 0.08, 0.48)

beta-gamma beta-gamma-delta

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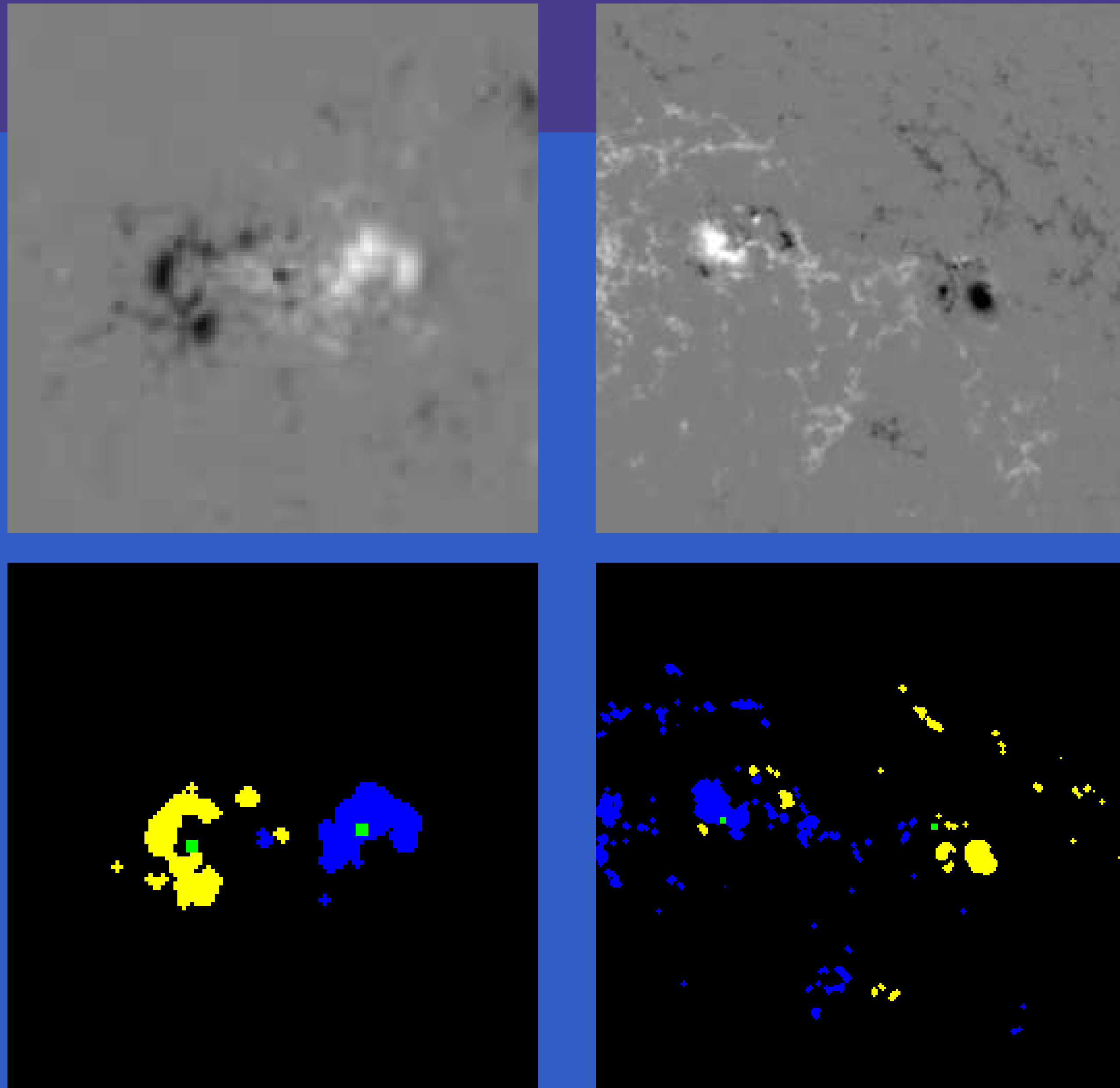

(1.10, 0.04, 0.53) (2.50, 0.92, 0.52)

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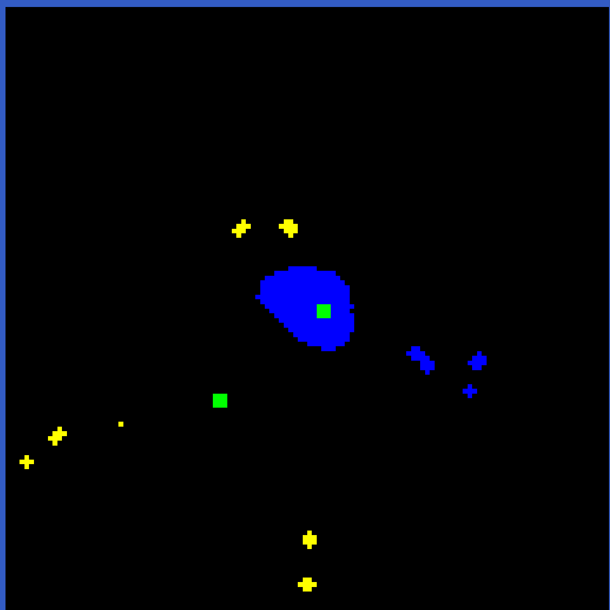

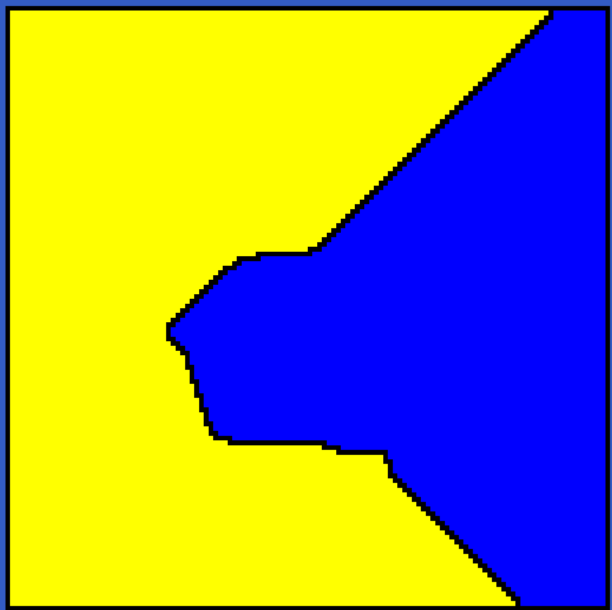

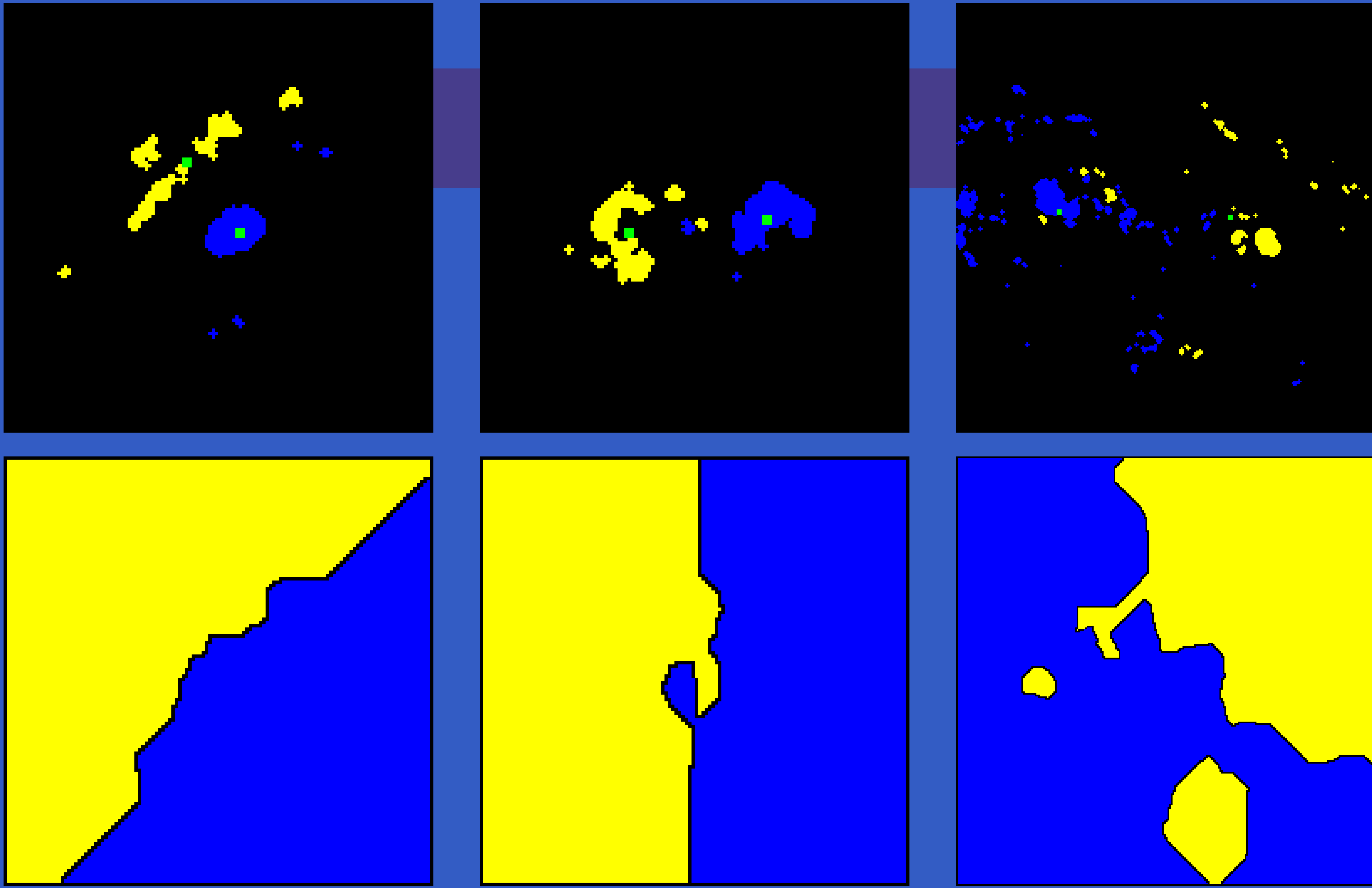

beta beta-gamma beta-gamma-delta

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- i.e., a total of 4 features for classification

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- for more info, see Breiman (2001)

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- remaining 38 (30%) as test data

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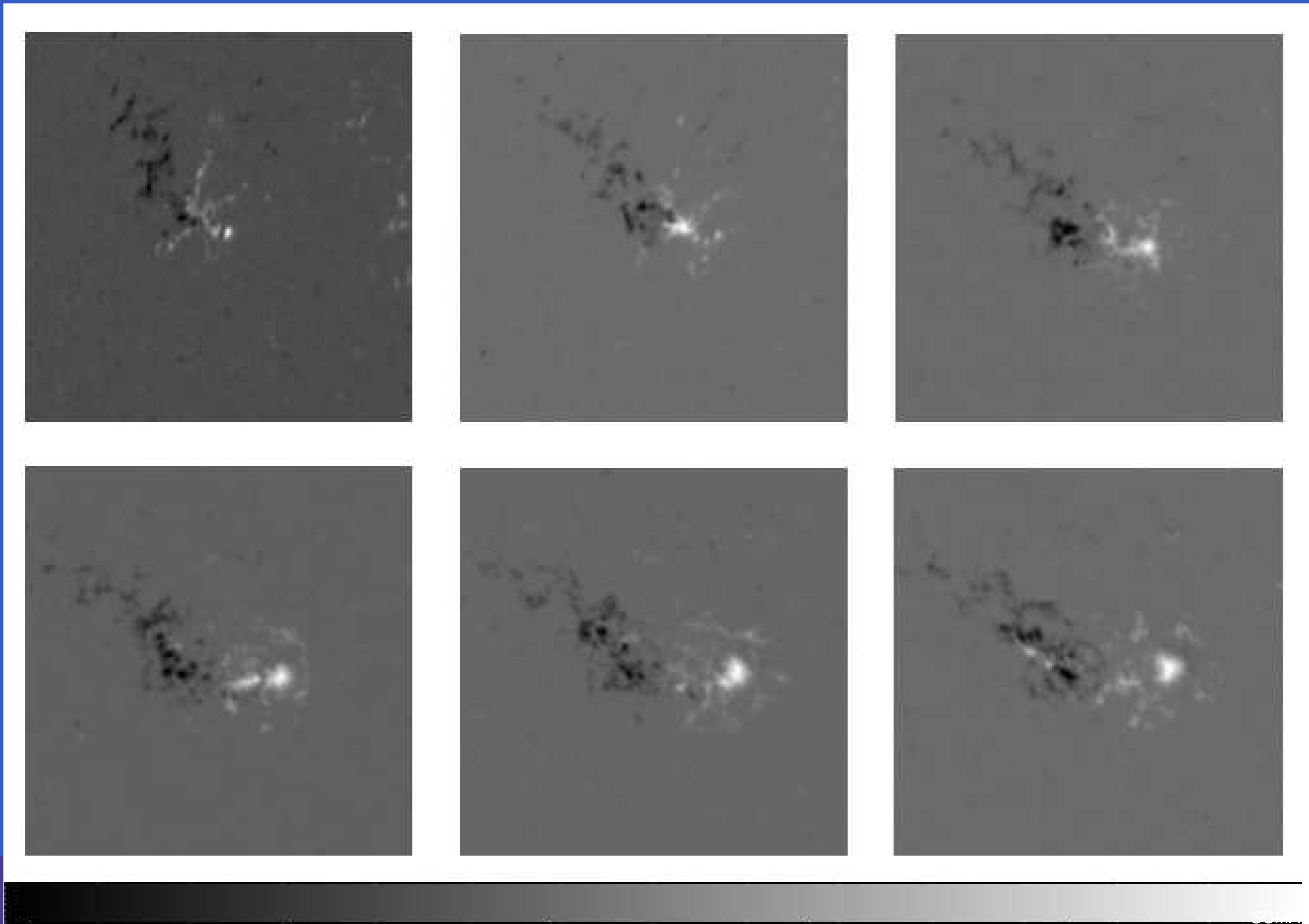
- (remember: we only used 4 features)

September 7 to 12, 1997



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1. amount of overlap between the convex hulls of the white and black sunspots (measuring how much the two polarities are “mixed” together)
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	actual			
predicted	α	β	$\beta\gamma$	$\beta\gamma\delta$
α	7	3	2	1
β	2	20	1	1
$\beta\gamma$	0	2	2	3
$\beta\gamma\delta$	0	0	0	1

Outline

Title: Automatic Detection and Classification of Sunspot Images

1. Background and Goal
2. Solution - two stages:
   (a) Detection
   (b) Features for Classification
      - spatial complexity measure
      - roughness of separating line
3. Automatic Classification Results
4. Future Work

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  - involve target tracking methodology

Thank You!