Scale Selective Extended Local Binary Pattern For Texture Classification

Yuting Hu, Zhiling Long, and Ghassan AlRegib

Multimedia & Sensors Lab (MSL)

Georgia Institute of Technology

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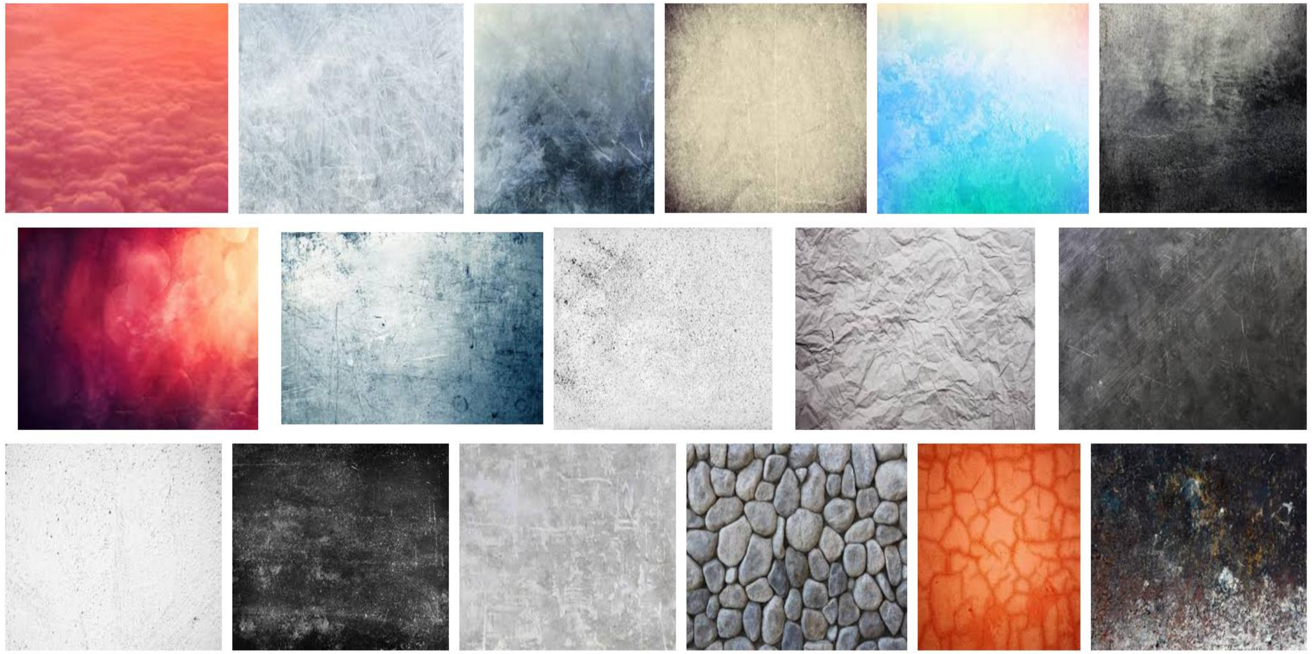
Outline

- Texture Representation and Its Challenge
- Proposed Local Descriptor, SSELBP
- Experimental Results
- Conclusion

Texture Definition

- Definition of texture[1]:
  - The feel or shape of a surface or substance such as smoothness, roughness, and softness
- Texture is everywhere.



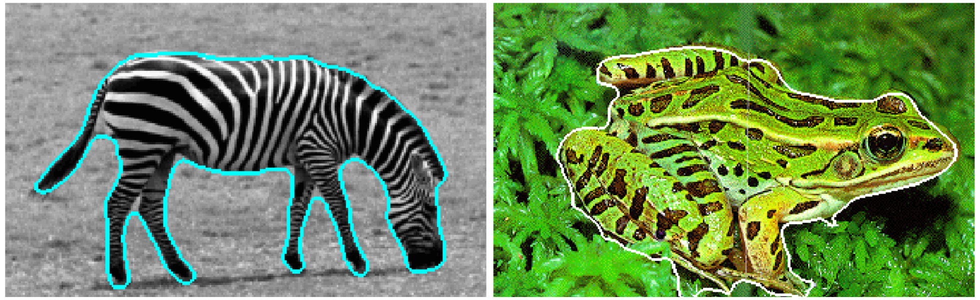


[1]: https://en.wiktionary.org/wiki/texture

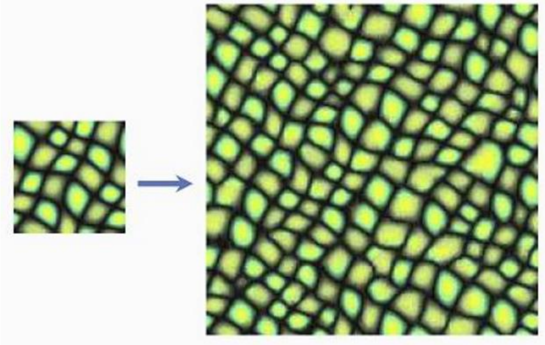
Why are Textures Important?

Classification/Retrieval [1]

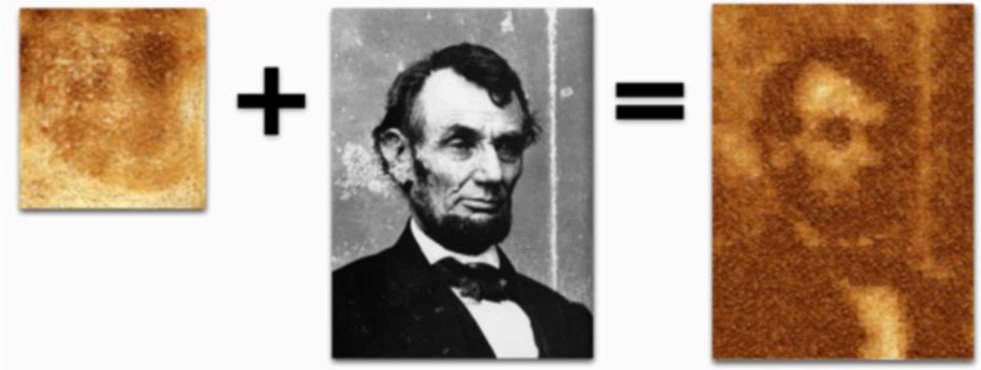
Segmentation [2]



Synthesis [3]

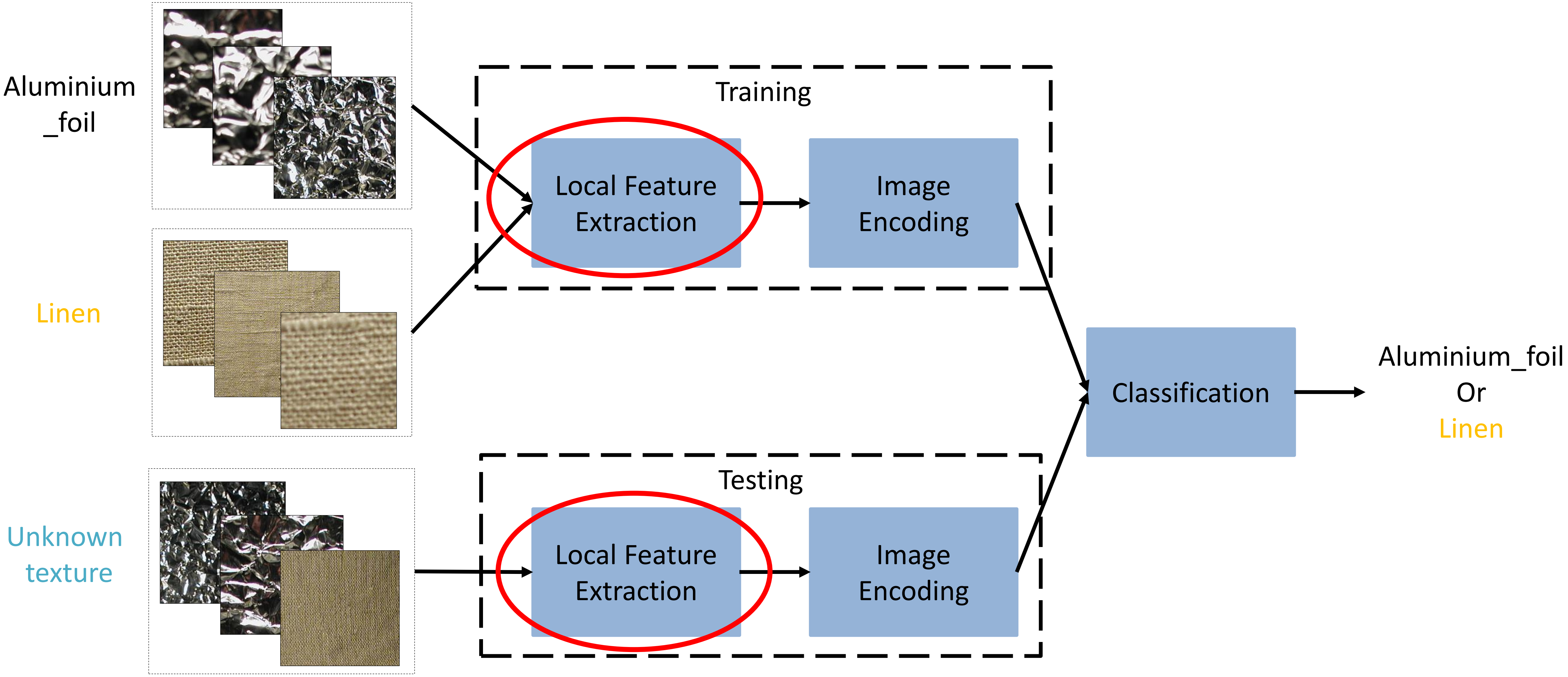


Transfer [4]



[1] http://www.robots.ox.ac.uk/~vgg/research/texclass/
[2] https://www.vis.uni-stuttgart.de/nc/lehre/details/typ/vorlesung/1767/98.html
[3] http://cs.brown.edu/courses/cs129/results/proj4/kgao/
[4] https://graphics.stanford.edu/~mdfisher/TextureSynthesis.html

Pipeline for Texture Classification



Texture Representation

- Local feature descriptors
  - Handcrafted local descriptors
    - Gray Level Co-occurring Matrix (GLCM)
    - Markov Random Field (MRF)
    - Filter Banks
    - Scale-invariant Feature Transform (SIFT)
    - Speed-up Robust Features (SURF)
    - Local Binary Pattern (LBP)
    - Orientated FAST and Rotated BRIEF (ORB)
  - CNN local descriptors

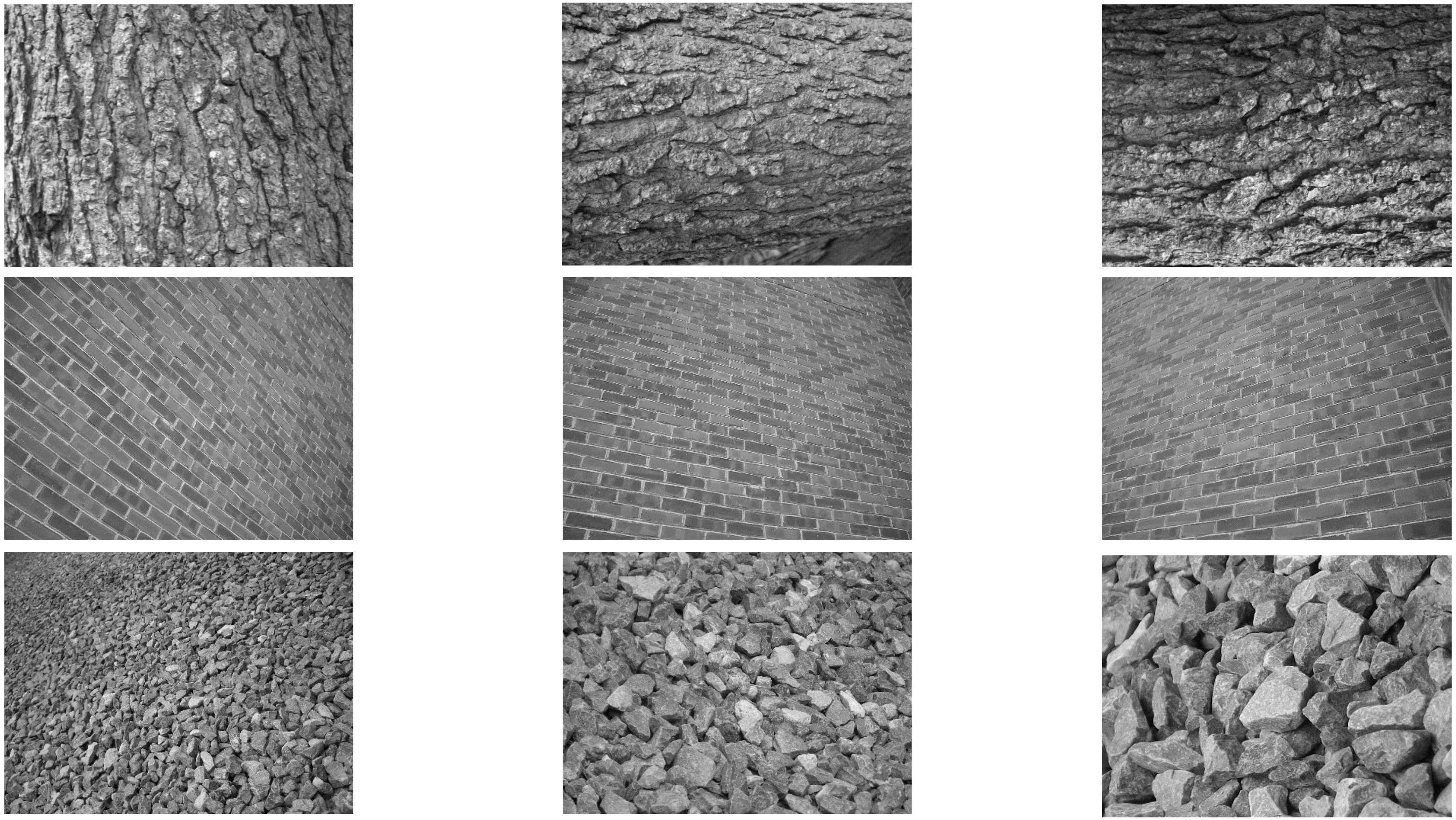
Challenges in Texture Representation

- Illumination, rotation, and scale variations

Illumination

Rotation

Scale



[1]: Y. Xu, H. Ji, and C. Ferm¨uller, "Viewpoint invariant texture description using fractal analysis," International Journal of Computer Vision, vol. 83, no. 1, pp. 85–100, 2009.

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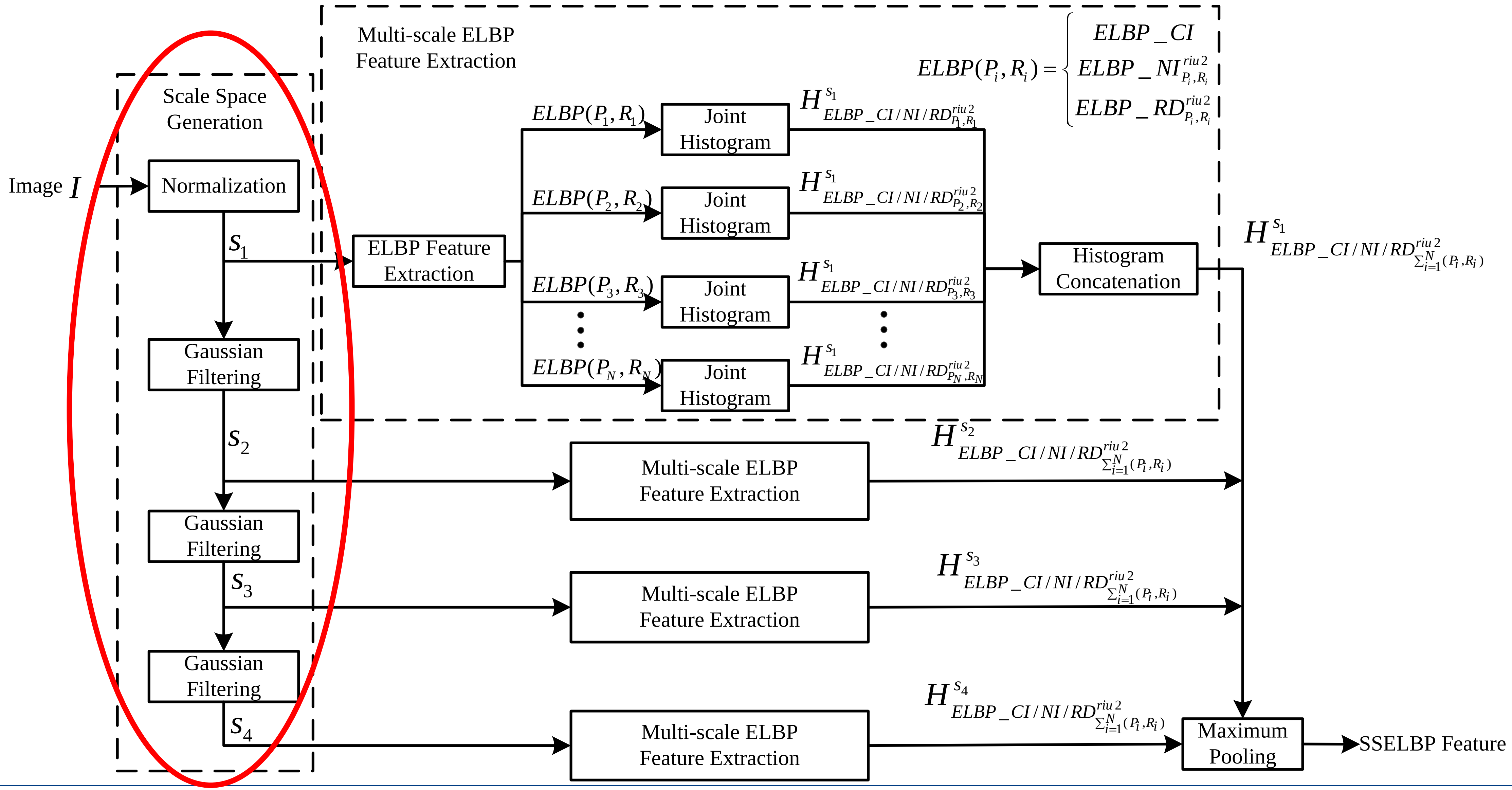
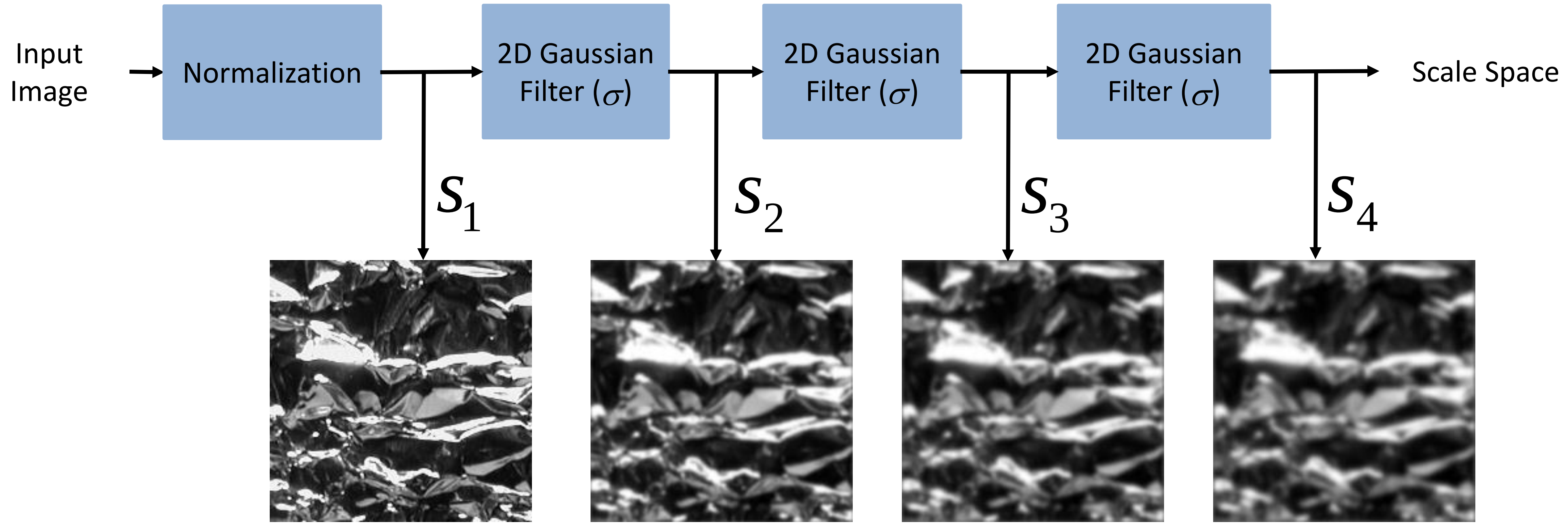
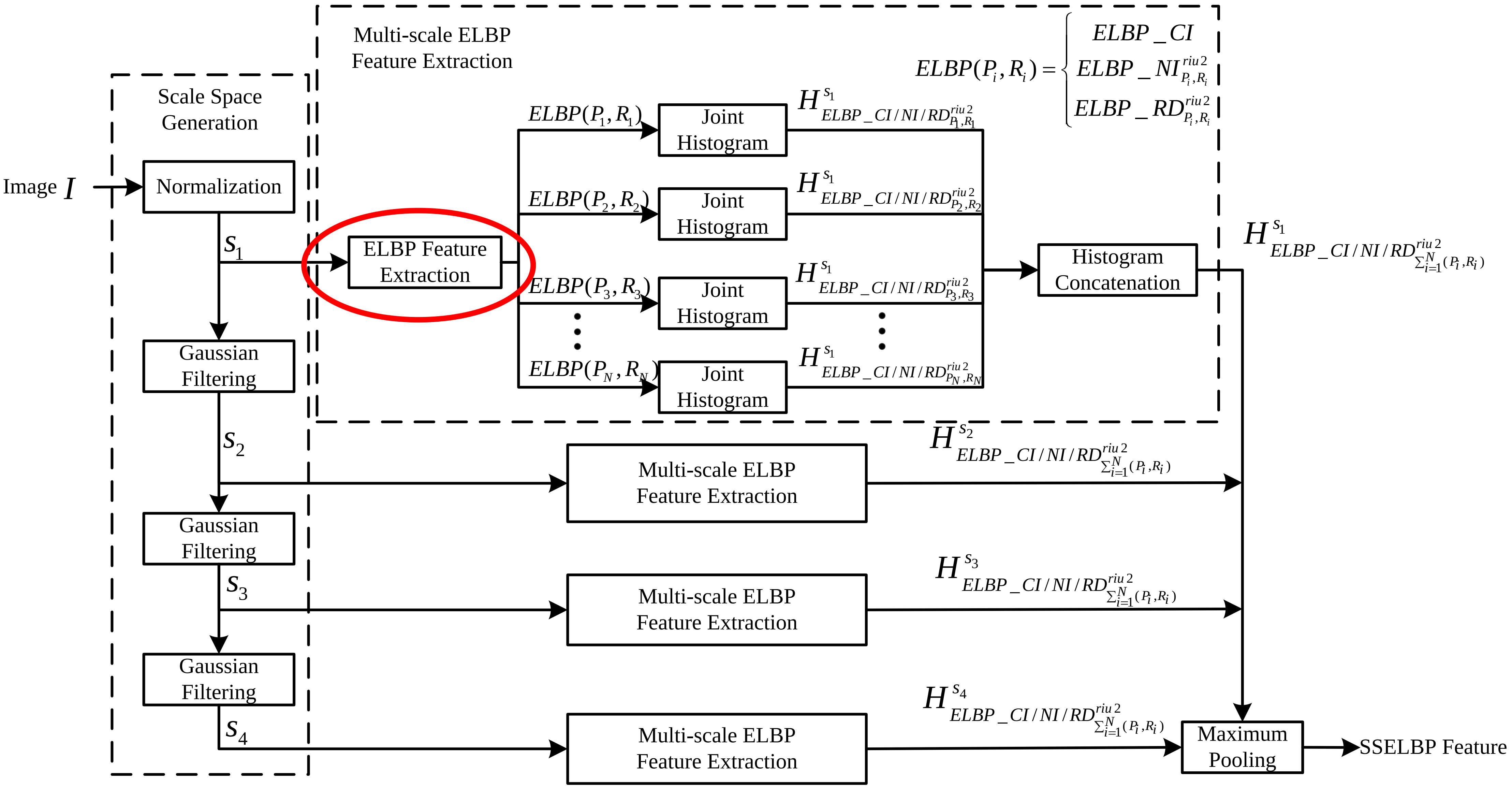
The Framework of SSELBP



Scale Space Generation



The Framework of SSELBP



Extended Local Binary Pattern (ELBP) Feature Extraction

- Global Sign Pattern

$$ELBP\_CI(x_c) = s(g_c - c_I), s(x) = \begin{cases} 1, \text{ if } x \geq 0 \\ 0, \text{ if } x < 0 \end{cases}.$$

- Neighboring Intensity Pattern

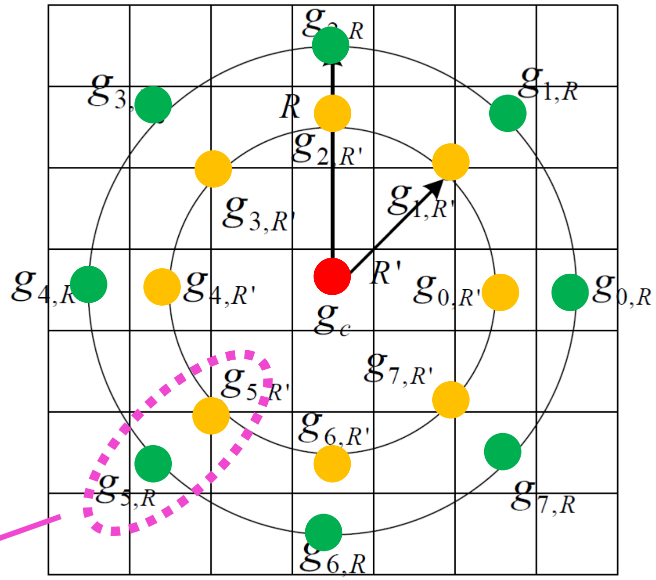
$$ELBP\_NI_{P,R}(x_c) = \sum_{p=0}^{P-1} s(g_{p,R} - u_R) \cdot 2^p$$

$$= \sum_{p=0}^{P-1} s\left(g_{p,R} - \frac{1}{P}\sum_{p=0}^{P-1} g_{p,R}\right) \cdot 2^p.$$

- Radial Difference Pattern

$$ELBP\_RD_{P,R}(x_c) = \sum_{p=0}^{P-1} s(g_{p,R} - g_{p,R'}) \cdot 2^p.$$

Example: $P = 8$

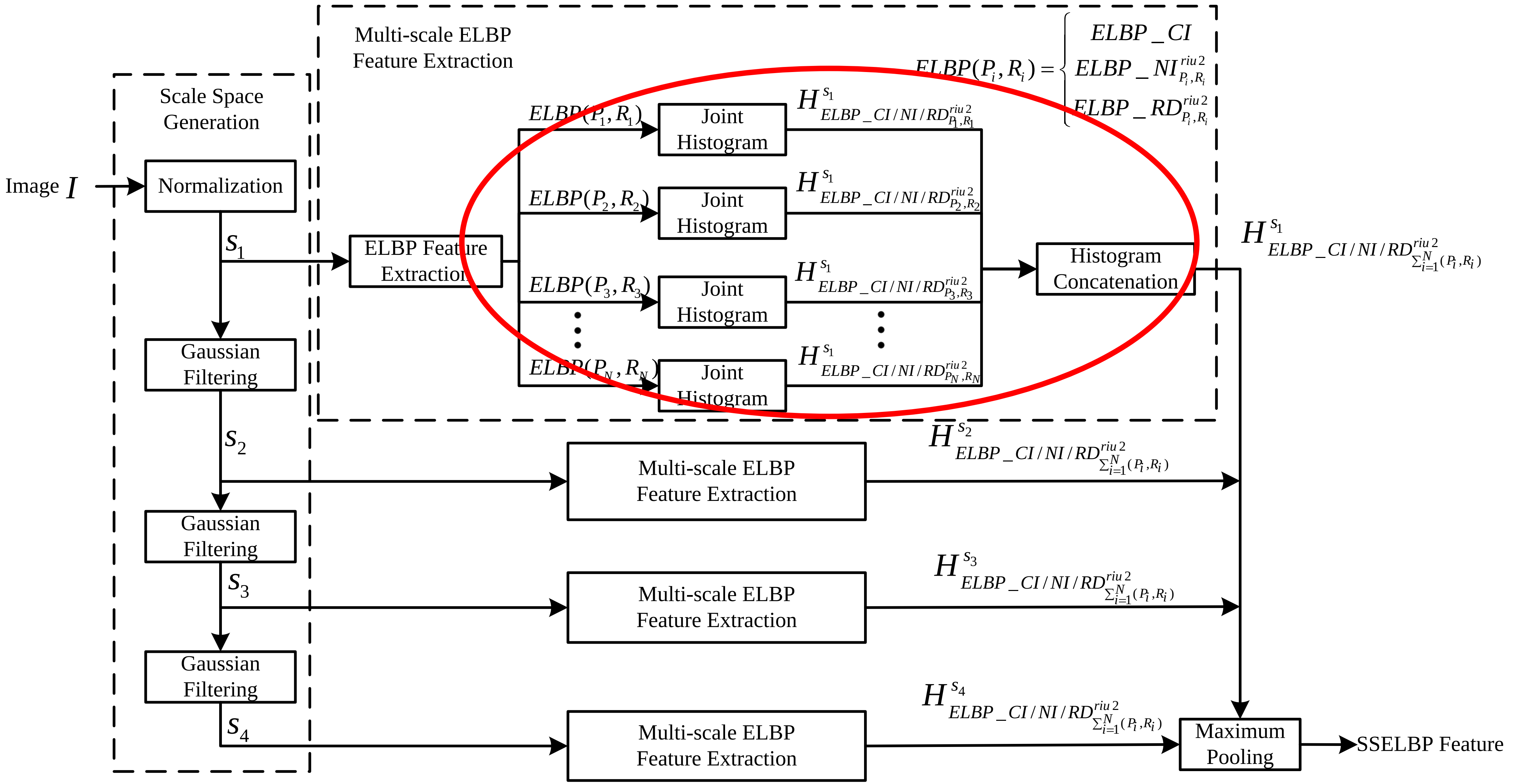


Rotation-invariant and uniform-2 (“riu2”)

Illumination and Rotation Invariance

[1]: L. Liu, L. Zhao, Y. Long, G. Kuang, and P. Fieguth, “Extended local binary patterns for texture classification,” Image and Vision Computing, vol. 30, no. 2, pp. 86–99, 2012.

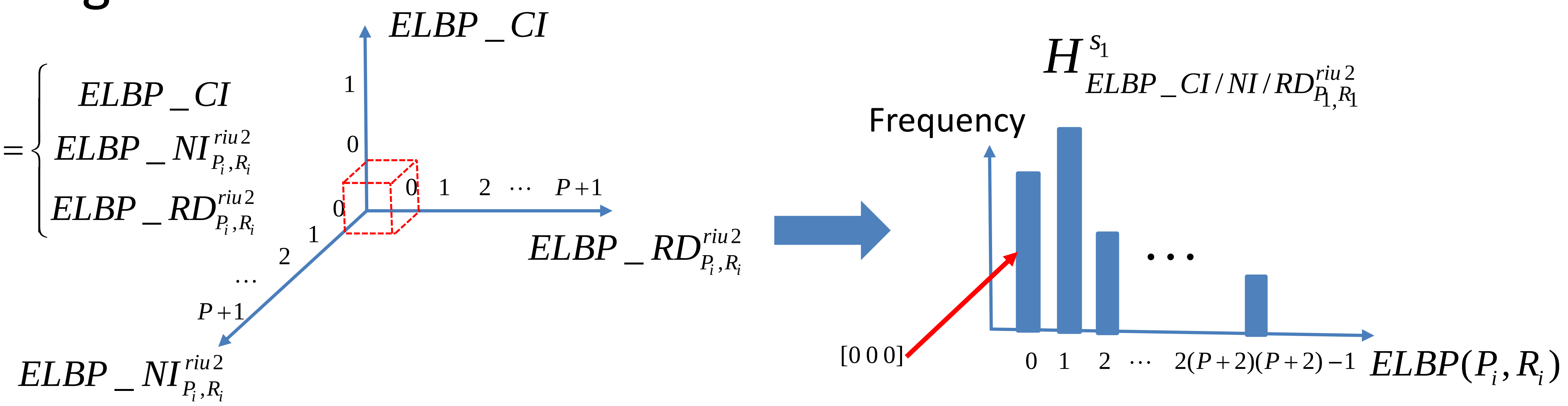
The Framework of SSELBP



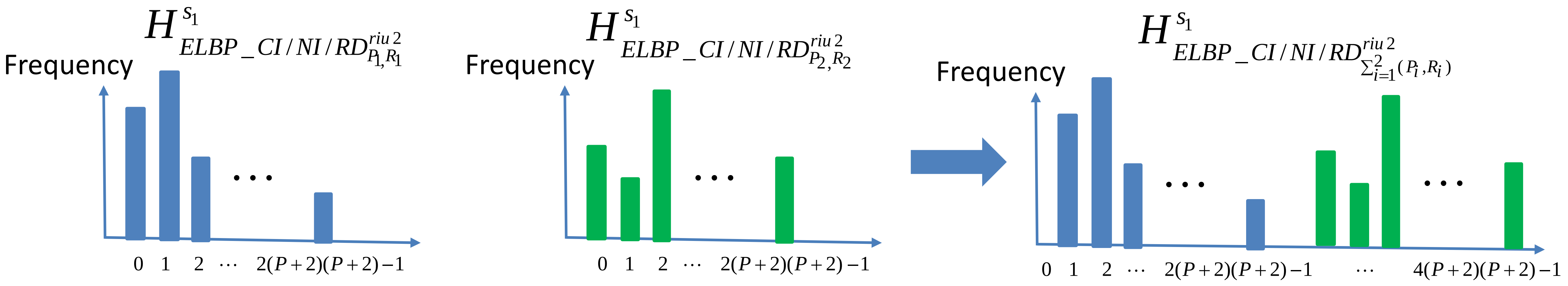
Single-scale- and Multi-scale- ELBP Histogram

- Joint Histogram

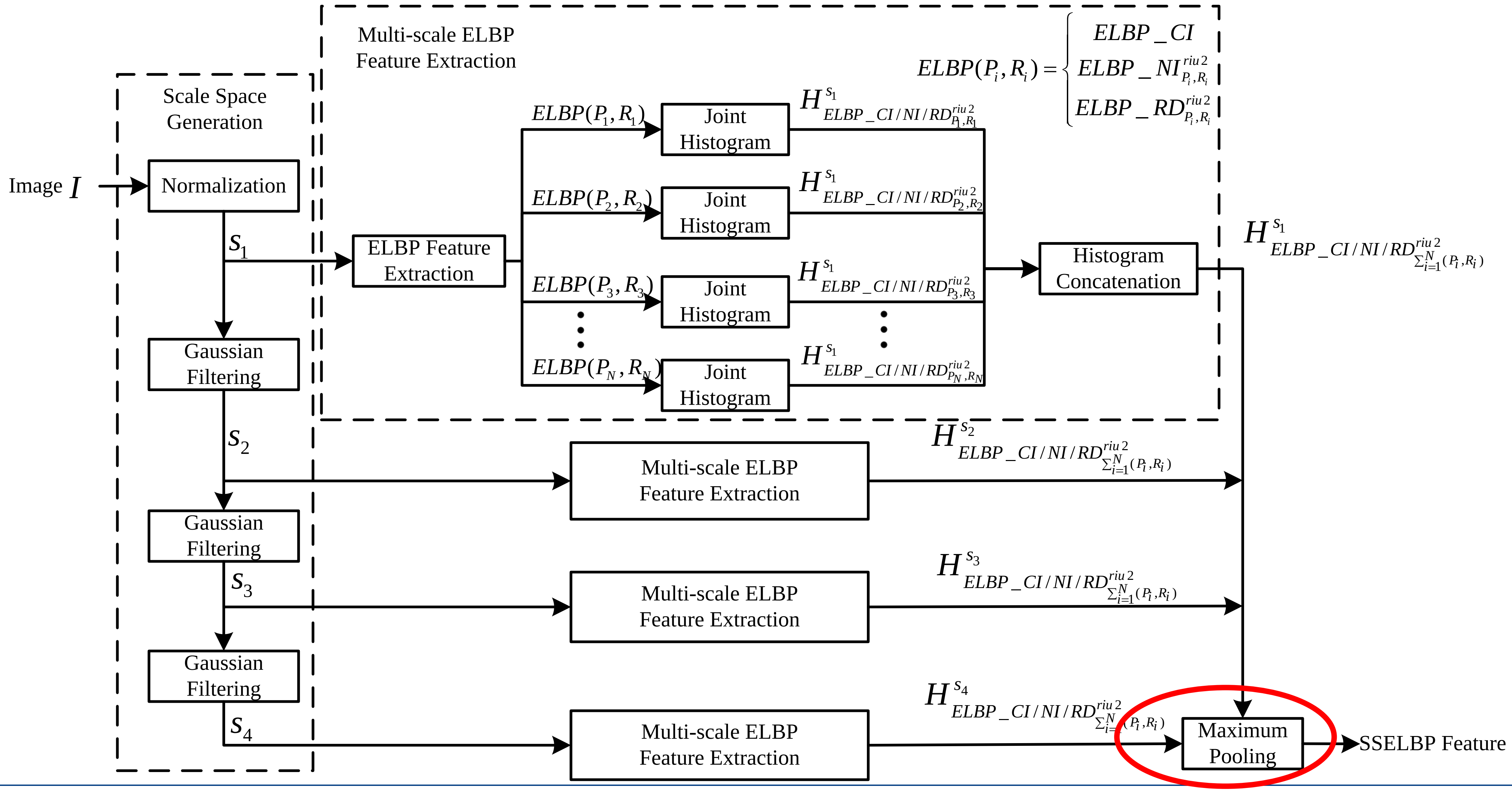
$$ELBP(P_i,R_i)=\begin{cases} ELBP\_CI \\ ELBP\_NI^{riu2}_{P_i,R_i} \\ ELBP\_RD^{riu2}_{P_i,R_i} \end{cases}$$



- Concatenated Histogram

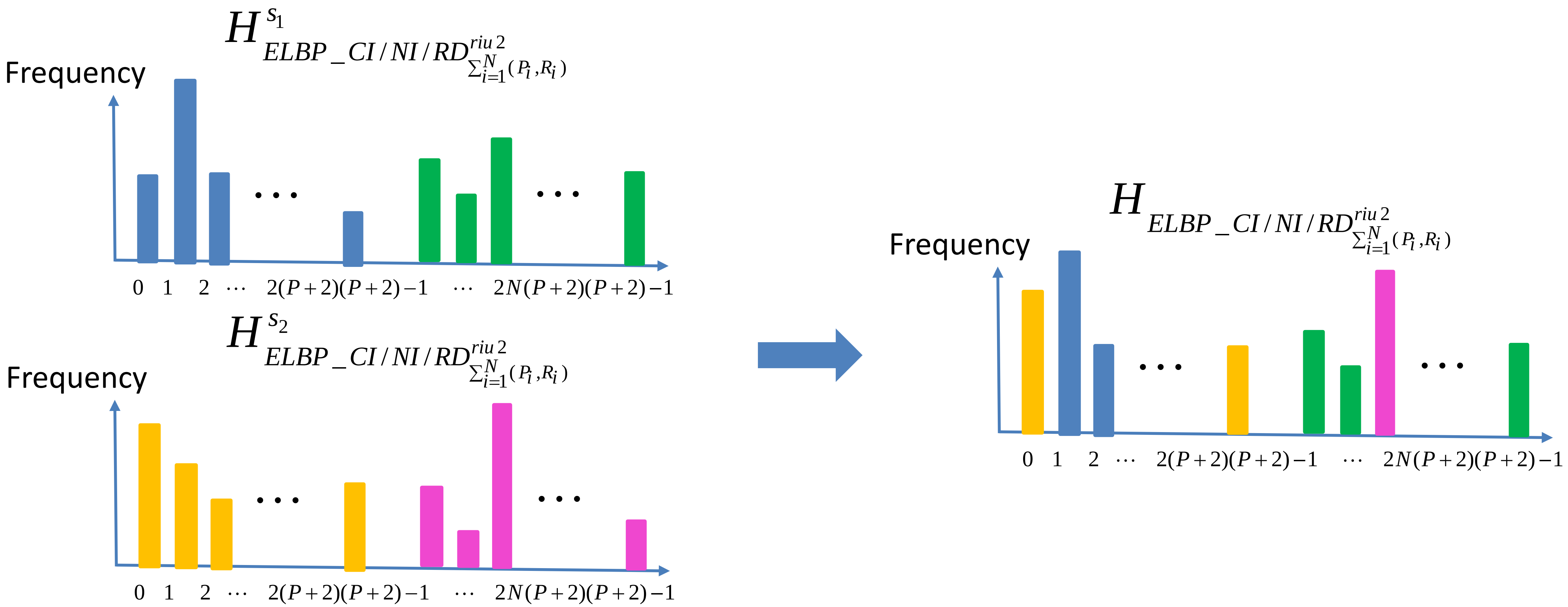


The Framework of SSELBP

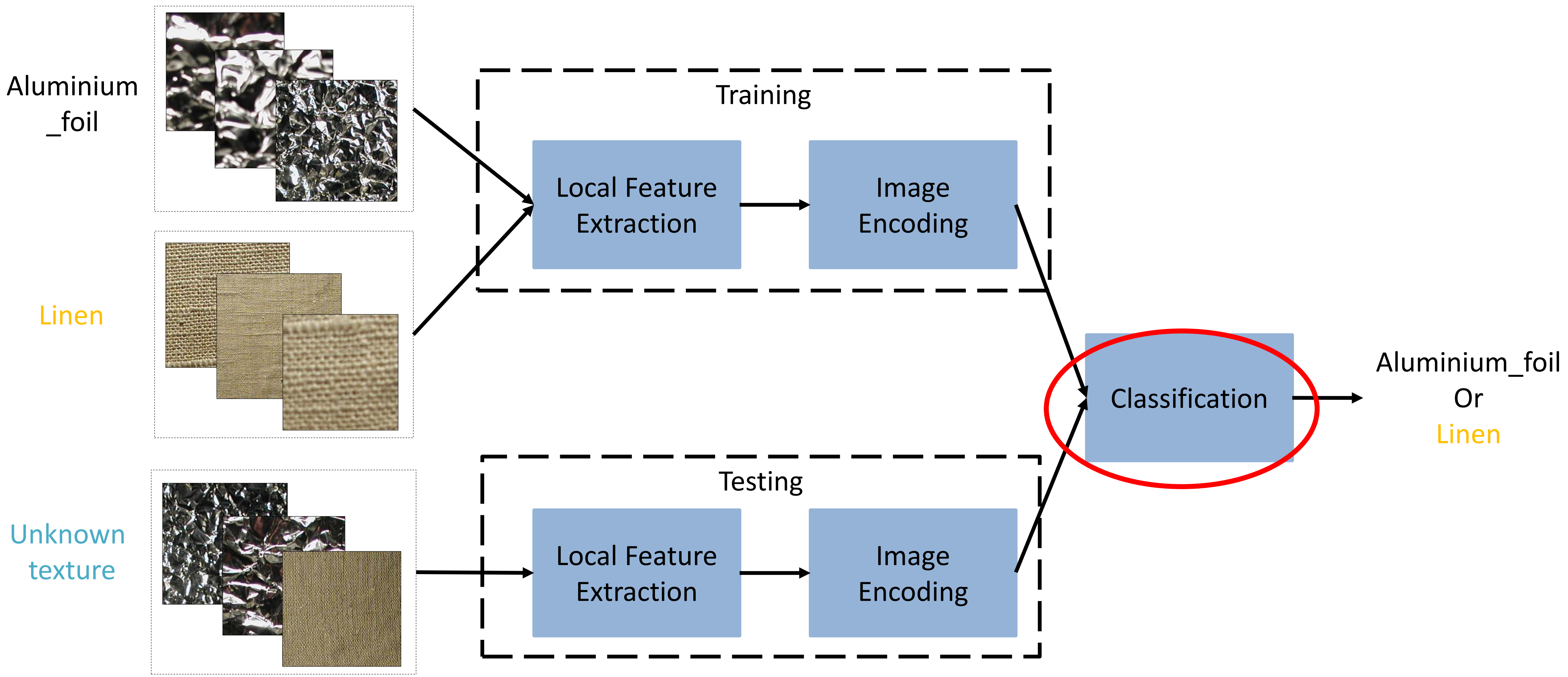


Maximum Pooling

$$H_{ELBP\_CI/RD/NI_{\sum_{i=1}^{N}(P_i,R_i)}} = \max_{l=1,2,\cdots,L}\left(H^{s_l}_{ELBP\_CI/RD/NI^{riu2}_{\sum_{i=1}^{N}(P_i,R_i)}}\right).$$



Pipeline for Texture Classification



Nearest Neighbor Classifier (NNC)

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Chi-square distance between histogram T and M :

$$D(T, M) = \sum_{n=1}^{N} \frac{(T_n - M_n)^2}{T_n + M_n}$$

T_n and M_n are the values of T and M at the n-th bin

Nearest neighbor classifier (NNC):

The class label of a test image is determined by the training image that has the minimal chi-square distance to the test image.

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Test Databases: KTHTIPS

[1]: E. Hayman, B. Caputo, M. Fritz, and J. Eklundh, “On the significance of real-world conditions for material classification,” in European Conference on Computer Vision (ECCV), 2004, pp. 253–266.

Experimental Results

Table 1: Classification accuracy (%) of the proposed SSELBP using different sampling schemes on the KTH-TIPS database.

Number of Radius, *N*	Maximum Accuracy (%)	Radius Selection for Maximum	Mean Accuracy (%)	Standard Derivation	Feature Dimension
1	96.44	(2)	94.80	1.56	200
2	97.86	(1,6)	97.04	0.63	400
3	98.09	(2, 5, 8)	97.51	0.43	600
4	98.11	(2, 3, 4, 7)	97.71	0.30	800
5	98.10	(1, 2, 3, 4, 8)	97.84	0.20	1000

Table 2: Classification accuracy (%) of the proposed SSELBP and typical texture descriptors on the KTH-TIPS and UMD databases. The number in the bracket following databases denotes the number of training samples used per class.

Classification Accuracy	KTH-TIPS (40)	UMD (20)
CLBP (Guo et al.)	97.19	98.00
RP (Liu et al.)	97.71	**99.13**
MRELBP (Liu et al.)	-	98.66
SSLBP (Guo et al.)	97.80	98.84
SSELBP (Proposed)	**98.11**	98.96

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Conclusion

- To characterize texture images with scale variations, we extracted local scale variant multi-scale ELBP features and then applied a global transformation.

- The **maximum pooling** strategy of **multi-scale ELBP histograms** generated from **a scale space** selected dominant scales and addressed scale variation issues for texture images.

- SSELBP achieved high accuracy comparable to typical texture descriptors on gray-scale-, rotation-, and scale-invariant texture classification but uses only **one third** of the feature dimension of CLBP or SSLBP.