

Removing specular reflection in multispectral dermatological images using blind source separation



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Proposed method

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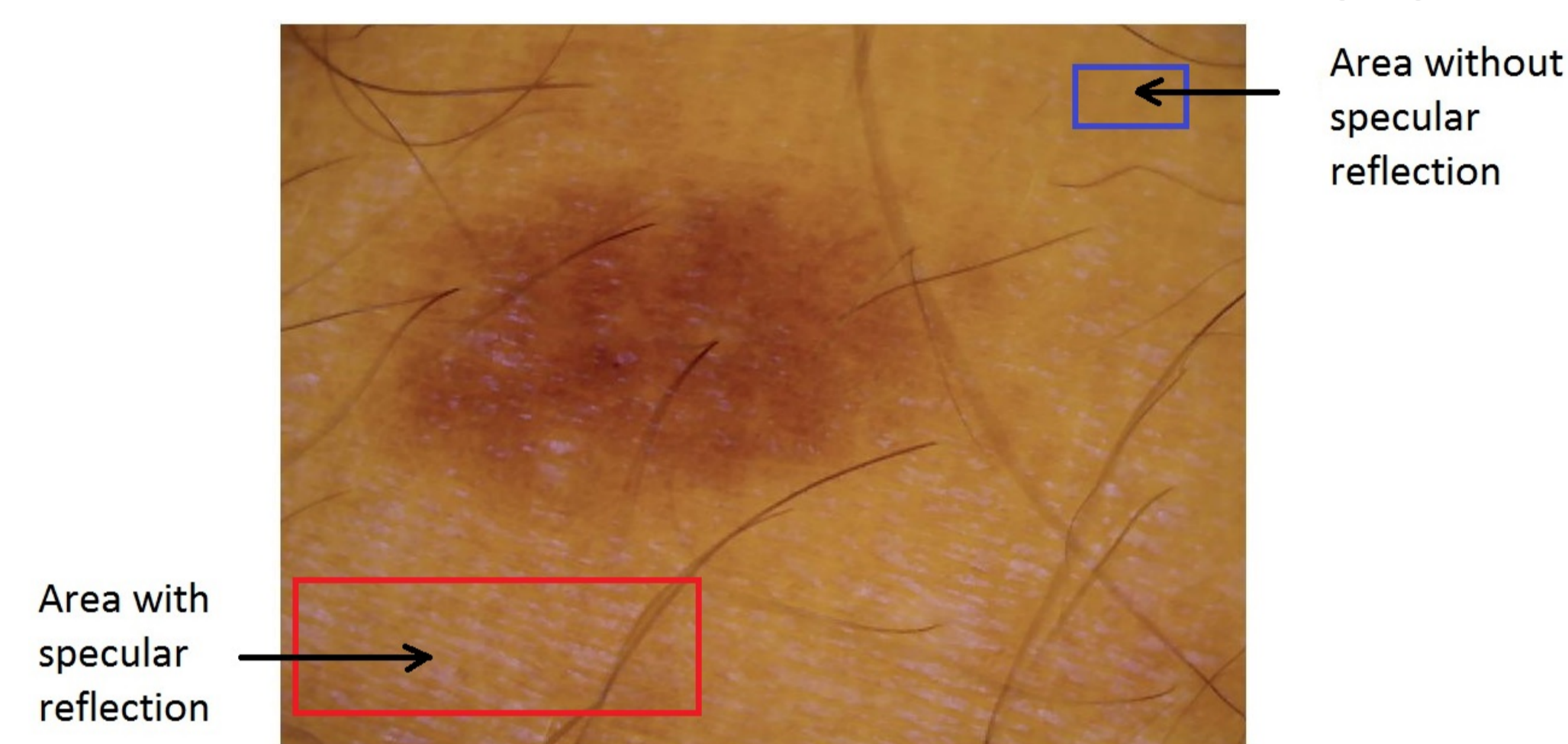
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Introduction

Nowadays, medical imaging has become an essential tool for diagnosing various human diseases, including those affecting the skin. One of these techniques which is more and more used and which showed its effectiveness is RGB imaging.



Problématique:

The specular reflection **disturbs** the extraction of useful information for dermatologists that is contained in the diffuse reflection.

Modelisation

$$I_i(\mathbf{u}) = I_{i,d}(\mathbf{u}) + I_{i,s}(\mathbf{u}), \quad 1 \leq i \leq 3$$

$$= w_d(\mathbf{u}) \cdot \int_{\Omega} E(\lambda) \sum_{j=1}^{N_d} \sigma_j(\mathbf{u}) \cdot f_j(\lambda) q_i(\lambda) d\lambda$$

$$+ w_s(\mathbf{u}) \cdot \int_{\Omega} E(\lambda) q_i(\lambda) d\lambda$$

- $w_d(\mathbf{u})$ represents the variation of shading,
- $E(\lambda)$ represents the intensity of the incident light,
- $q_i(\lambda)$ represents the sensitivity of the camera sensor around the wavelength λ_i ,
- Ω represents the spectral domain,
- $w_s(\mathbf{u})$ represents the specular component,
- N_d is the number of surface colours (diffuse colours),
- $f_j(\lambda)$ represents the basic functions of the reflectance,
- $\sigma_j(\mathbf{u})$ are the coefficients that depend on the surface colour.

$$I_i(\mathbf{u}) = \sum_{j=1}^{j=N_d+1} a_{ij} \cdot S_j(\mathbf{u}), \quad 1 \leq i \leq 3,$$

$$a_{ij} = \begin{cases} \int_{\Omega} E(\lambda) f_j(\lambda) q_i(\lambda) d\lambda & \text{pour } 1 \leq j \leq N_d \\ \int_{\Omega} E(\lambda) q_i(\lambda) d\lambda & \text{pour } j = N_d + 1 \end{cases}$$

$$S_j(\mathbf{u}) = \begin{cases} \sigma_j(\mathbf{u}) w_d(\mathbf{u}) & \text{pour } 1 \leq j \leq N_d \\ w_s(\mathbf{u}) & \text{pour } j = N_d + 1 \end{cases}$$

Proposed method

Vectorisation procedure :

$$x_i(v) = \text{vec}(I_i(\mathbf{u})) \text{ and } s_j(v) = \text{vec}(S_j(\mathbf{u})),$$

$$x_i(v) = \sum_{j=1}^{j=N_d+1} a_{ij} s_j(v), \quad i \in \{1, 2, 3\}.$$

Matrix formulation :

$$\mathbf{x}(v) = \mathbf{A} \cdot \mathbf{s}(v),$$

- $\mathbf{x}(v) = [x_1(v), x_2(v), x_3(v)]^T$,
- $\mathbf{s}(v) = [s_1(v), s_2(v), \dots, s_{N_d+1}(v)]^T$,
- $\mathbf{A} = (a_{ij})_{1 \leq i \leq 3, 1 \leq j \leq N_d+1}$.

Step 1: ICA

Algorithm :

- 1 Construction of the new vector of centred mixtures:
 $\tilde{\mathbf{x}}(v) = [\tilde{x}_1(v), \tilde{x}_2(v), \tilde{x}_3(v)]^T$,
- 2 Diagonalization of the matrix $\mathbf{R}_{\tilde{\mathbf{x}}}(0)$:
 $\mathbf{R}_{\tilde{\mathbf{x}}}(0) = E[\tilde{\mathbf{x}}(v) \cdot \tilde{\mathbf{x}}^T(v)] = \mathbf{V} \cdot \mathbf{E}_0 \cdot \mathbf{V}^T$
- 3 Spatial whitening of mixtures and determining N_d :
 $\mathbf{z}(v) = \mathbf{W} \cdot \tilde{\mathbf{x}}(v)$, where $\mathbf{W} = \mathbf{E}_0^{-\frac{1}{2}} \cdot \mathbf{V}^T$
- 4 Calculation of a matrix $\mathbf{R}_{\mathbf{z}}(\tau) = E[\mathbf{z}(v) \cdot \mathbf{z}^T(v - \tau)]$,
- 5 Diagonalization of the matrix $\mathbf{R} = \frac{1}{2} \{ \mathbf{R}_{\mathbf{z}}(\tau) + \mathbf{R}_{\mathbf{z}}^T(\tau) \}$:
 $\mathbf{R} = \mathbf{U} \cdot \mathbf{E}_{\tau} \cdot \mathbf{U}^T$
- 6 Estimating the separation matrix :
 $\mathbf{C} = \mathbf{U}^T \cdot \mathbf{W} = \mathbf{P} \mathbf{D} \cdot \mathbf{A}^{-1}$
- 7 Estimating the source matrix : $\mathbf{y}(v) = \mathbf{C} \cdot \mathbf{x}(v)$

However, as generally the working hypotheses of the ICA method cannot be verified perfectly by our sources, which means that we would instead have :

$$\mathbf{y}(v) = \mathbf{C} \cdot \mathbf{x}(v) = \mathbf{P} \mathbf{D} \cdot \mathbf{s}(v) + \mathbf{Error}.$$

Step 2: NMF

Decomposing the matrix $\mathbf{x}(v)$ into the product of two matrices

$$\mathbf{x}(v) = \mathbf{B} \cdot \mathbf{h}(v)$$

$$\mathbf{B} \simeq \mathbf{A} \text{ and } \mathbf{h}(v) \simeq \mathbf{s}(v).$$

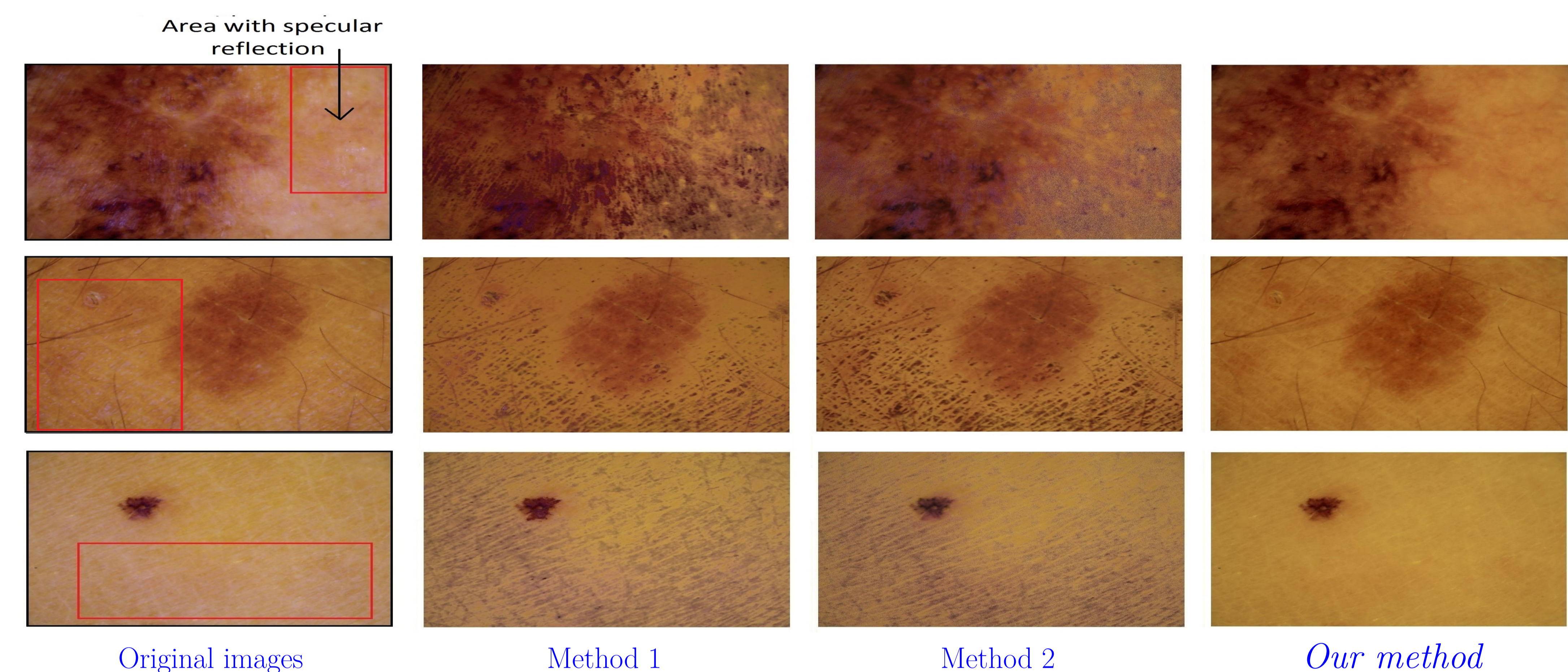
Algorithm :

- 1 Initialize $\mathbf{h}(v)$ by the matrix $\mathbf{y}(v)$ estimated by the ACI : $\mathbf{h}(v) = \mathbf{y}(v)$
- 2 While $D_{\text{euc}}(\mathbf{x}|\mathbf{B}\mathbf{h}) > \epsilon$, do
 - $\mathbf{B} = \mathbf{x}\mathbf{h}^T(\mathbf{h}\mathbf{h}^T)^{-1}$
 - Set to zero all negative elements of \mathbf{B}
 - $\mathbf{h} = (\mathbf{B}^T \mathbf{B})^{-1} \mathbf{B}^T \mathbf{x}$
 - Set to zero all negative elements of \mathbf{h}
 - $D_{\text{euc}}(\mathbf{x}|\mathbf{B}\mathbf{h}) = \frac{1}{2} \|\mathbf{x}(v) - \mathbf{B} \cdot \mathbf{h}(v)\|^2$

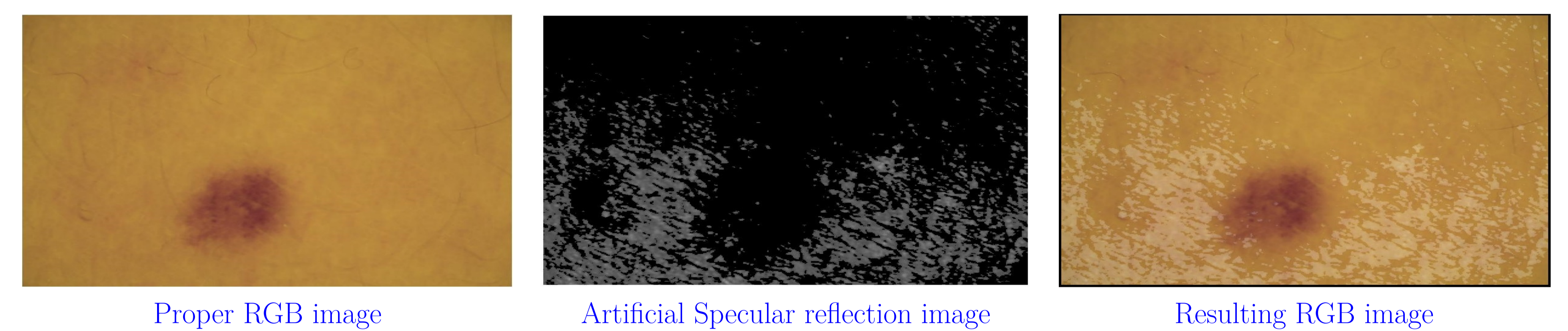
Results

We evaluate the performance of our method by comparing it to the two methods that have been proposed respectively in [1] and [2] using the database of multi-spectral dermatological images which is available in [3]. We mention that the first method [1] is a method based on image processing techniques while the second method [2] is a method based on blind source separation.

Real dermatological images



Artificial dermatological images



Signal-to-Interference Ratio criterion :

$$SIR = 10 \cdot \log_{10} \left(\frac{E[s_3(v)^2]}{E[(s_3(v) - h_3(v))^2]} \right)$$

| | Method [1] | Method [2] | | | Our method |
|---------------|------------|------------|--------------|-----------|--------------|
| | | $N_d = 1$ | $N_d = 2$ | $N_d = 3$ | |
| SIR (dB) | 2.31 | 12.58 | 18.60 | 12.55 | 41.60 |
| σ (dB) | 7.38 | 5.51 | 12.36 | 11.37 | 0.19 |

References

- [1]. Yang, Q., Wang, S., Ahuja, N.: Real-time specular highlight removal using bilateral filtering. In: European conference on computer vision. pp. 87–100. Springer (2010)
- [2]. Madooei, A., Drew, M.S.: Detecting specular highlights in dermatological images. In: 2015 IEEE International Conference on Image Processing (ICIP). pp. 4357–4360. IEEE (2015)
- [3]. Lézoray, O. : <https://lezoray.users.greyc.fr/researchDatabasesDermoscopy.php>

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