Mediterranean Smart Cities Conference (MSCC 2024)
2-4 May, 2024, Martil, Morocco

Multimodal Markov Fields Approach for Enhanced Segmentation of Aerial Images: Statistical Integration of CIEDE2000 Color Difference, Texture Features, and Edge Information

Jamal Bouchti
Optique and Photonic Team
Faculty of Sciences, Abdelmalek Essaadi university
Tetuan 93002, Morocco
jamalbouchti@gmail.com

Ahmed Bendahmane
Department of Computer Science
ENS , Abdelmalek Essaadi university
Tetuan 93002,Morocco
abendahman@uae.ac.ma

Adel Asselman
Optique and Photonic Team
Faculty of Sciences,M'hannech II,
Tetuan 93002,
Morocco
adelasselman@gmail.com

***Abstract*—Aerial images, captured by drones, satellites, or aircraft, are omnipresent in diverse fields, from mapping and surveillance to precision agriculture. The efficacy of image analysis in these domains hinges on the quality of segmentation, and the precise delineation of objects and regions of interest. In this context, leveraging Markov fields for aerial image segmentation emerges as a promising avenue. The segmentation of aerial images presents a formidable challenge due to the variability in capture conditions, lighting, vegetation, and environmental factors. To meet this challenge, our work proposes an innovative method harnessing the power of Markov fields by integrating a multimodal energy function. This energy function amalgamates key attributes, including color difference measured by the CIEDE2000 metric, texture features, and detected edge information. The CIEDE2000 metric, derived from the CIELab color space, is renowned for its ability to measure color difference more consistently with human perception than conventional metrics. By incorporating this metric into the energy function, our approach enhances sensitivity to subtle color variations crucial for aerial image segmentation. Texture, a vital attribute characterizing regions in aerial images, offers crucial insights into terrain or objects. Our method incorporates texture features to refine the separation of homogeneous regions. Contours, playing a fundamental role in segmentation, are identified using an edge detector to pinpoint boundaries between regions of interest. This information is integrated into the energy function, elevating contour consistency and segmentation accuracy. This article comprehensively presents our methodological approach, the conducted experiments, obtained results, and a thorough discussion of the method's advantages and limitations.**

Keywords*— Image segmentation; Multimodal Markov Fields Statistical Integration; CIEDE2000 Color Difference; Texture Features; Edge Information

I. Introduction

Aerial images, obtained from drones, satellites or aircraft, have become ubiquitous in many disciplines, from mapping and surveillance to precision agriculture and urban planning. However, effective analysis of these images depends largely on the quality of the segmentation, i.e. the precise delineation of objects and regions of interest. In this context, the use of Markov fields for the segmentation of aerial images has become a promising approach. Segmentation of aerial images is a complex challenge due to the variability of capture conditions, lighting, vegetation, and other environmental factors. To address this challenge, our work aims to propose an innovative method that exploits the power of Markov fields by incorporating a multimodal energy function. This energy function combines several key attributes, including color difference based on the CIEDE2000 metric, texture features, and detected edge information. The CIEDE2000 metric, derived from CIELab color spaces, is widely recognized for its ability to measure color difference in a way that is more consistent with human perception than conventional metrics. By incorporating this measure into the energy function, it is possible to take better account of subtle variations in color, which is essential for the segmentation of aerial images. Texture is an important attribute for characterizing regions in aerial images, as it can provide crucial information about the nature of the terrain or objects. Our method incorporates texture features to improve the separation of homogeneous regions. In addition, contours play a fundamental role in segmentation. We therefore use an edge detector to identify the boundaries between the regions of interest. This information is incorporated into the energy function to improve the consistency of the contours and the accuracy of the segmentation. In this article, we present in detail our methodological approach, the experiments carried out, the results obtained, and an in-depth discussion of the advantages and limitations of our method. This research opens up new perspectives for the analysis of aerial images in various application domains.

Fig.1. Aerial Image

II. THEORETICAL FOUNDATIONS

Successful segmentation of aerial imagery relies on a solid theoretical foundation, integrating a variety of techniques and measurements. In this section, we will explore the essential theoretical underpinnings of our multimodal segmentation approach. Segmenting an image Y involves dividing all the pixels S into homogeneous regions: $S = S_1 \cup S_2 \cup \ldots \cup S_K$

We introduce the label map (X_s, $s \in S$) to represent a partition: pixel $s \in S_j \Leftrightarrow X_s = j$.

The probabilistic modelling approach to the segmentation problem consists of :

- Consider the image $Y = (Y_s)$ and the label map $X = (X_s)$ (to be constructed) as random variables governed by a statistical law π;
- propose a modelling ≡ define such a law π;
- With X and Y linked by the law π, and Y given, reconstruct or estimate X using π and Y.

Note that if the law of image formation F :

$$X = (X_s) \text{ a } Y = (Y_s) = F(X)$$

If it were completely known, all we had to do was invert F! Such a deterministic function F is unrealistic, because the mechanism of image formation is complex, to say the least, and is marred by noise, i.e. the randomness or handling errors that occur. The probabilistic model approach defines passages by conditional statistical laws. Markov fields are some of the most widely used examples of such laws.

A. *Markov fields in image segmentation*

Markov fields are a powerful mathematical framework widely used in computer vision [1], particularly for image segmentation[2]. They provide a structured way of modelling the spatial dependencies between pixels in an image. In a segmentation context, Markov fields are used to capture the spatial regularity of regions of interest. More specifically, they model the neighborhood relationships between pixels and facilitate the propagation of information about whether pixels belong to a particular class. We then define the notion of neighborhood [3], which designates a set of pixels located around a central pixel. Consider a pixel S whose position in the image is given by the coordinates (m, n). Its affix is therefore s = (m, n). A neighborhood of S, denoted V(S), is defined as a set of connected pixels P' defined by:

$$N(i,j) = \left\{ (k,l) \mid 0 < (k-i)^2 + (l-j)^2 < constant \right\}$$

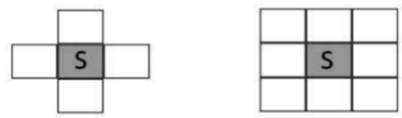

Fig. 2. 4 and 8 neighborhoods

A clique is any subset A of sites that are mutual neighbors. Examples of cliques are shown in the figure below:

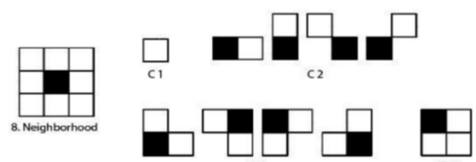

Fig. 3. Cliques for 8 neighborhoods

- Gibbs distribution:

Gibbs fields are commonly used to model thermodynamic systems in statistical physics. The Gibbs distribution is a central concept in MRFs. This equivalence means that the interaction potential between random variables follows a Gibbs distribution[4]. This makes it possible to describe the interactions between the variables in a coherent way, while maintaining the notion of spatial dependence[5].

- Hammersley-Clifford theorem:

The Hammersley-Clifford theorem is a result in probability theory, mathematical statistics and statistical mechanics that gives the necessary and sufficient conditions under which a strictly positive probability distribution (of events in a probability space) can be represented as events generated by a

Markov random field [6].This is the fundamental theorem of random fields, which states that a probability distribution with strictly positive mass or density satisfies one of the Markov properties with respect to an undirected graph G if and only if it is a Gibbs random field, i.e. its density can be factored over the cliques (or complete subgraphs) of the graph. In other words, this theory states that the probability of a configuration of states depends mainly on the local relationships between the random variables in the field[7].

B. CIEDE2000 Color Difference

The CIEDE2000 metric, derived from CIE Lab color spaces, plays a central role as a color attribute in our approach. Designed to measure color difference more accurately[8], CIEDE2000 takes into account the non-linearities of human perception of color. It subtly captures variations in hue, saturation and luminosity, offering a more robust measurement of color difference than its predecessors[9].The individual components of this formula are as follows:

$$\Delta E_{00} = \sqrt{(\Delta L'/K_L S_L)^2 + (\Delta C'/K_C S_C)^2 + (\Delta H'/K_H S_H)^2 + RT(\Delta C'/K_C S_C)(\Delta H'/K_H S_H)}$$

Where :
$\Delta L'$, $\Delta C'$, $\Delta H'$: ': Difference in luminance , chroma and Hue between Lab_1 and Lab_2.
The S_L, S_C and S_H components are adjustment factors to take account of non-linearities in the perception of color by the human eye:
The k_L, k_C and k_H values are parameters that depend on the luminance of the sample and the color of the average sample.
RT is an additional correction factor.
Integrating the CIEDE2000 metric into our energy function enables more accurate segmentation by considering the subtle nuances of color present in aerial images.

C. Texture as a Segmentation Attribute

Texture is an essential element for characterizing regions of interest in aerial images. It represents the repetition of patterns or structures and can provide crucial information about the nature of the terrain or objects.

- Co-occurrence matrix in the HSV Space:

The co-occurrence matrix, also known as the correlation matrix, is a powerful image processing technique that quantifies the spatial relationships of grey levels or pixel values in an image. The co-occurrence matrices contain a very large amount of information and are therefore difficult to manipulate. For this reason, fourteen indices (defined by Haralick)[10] which correspond to descriptive characteristics of textures can be calculated from these matrices. In the context of our study, we take an innovative approach using the HSV (Hue, Saturation, Value) color space. Specifically, we focus on the hue (Hue) and intensity (Value) components. Hue represents color tone, while intensity captures luminance. We aim to exploit these two components to assess the homogeneity and correlation of textures in aerial images.

- Homogeneity:

the more we find the same pair of pixels, the higher this index is, for example a uniform image, or a texture that is periodic in the direction of translation.

$$Homogeneity = \sum_{i=1}^{q-1}\sum_{j=1}^{q-1}\frac{P(i,j)}{1+|i-j|}$$

Fig. 4. Homogeneity result.

- Correlation:

describes the correlations between the rows and columns of the cooccurrence matrix.

$$Correlation = \sum_{i=1}^{q-1}\sum_{j=1}^{q-1}\frac{ijP(i,j)-u_i u_j}{\sigma_i \sigma_j}$$

Fig.5. Correlation Result

The co-occurrence matrix in HSV space allows us to analyze how hue and intensity values covary within a local image window. This approach is essential for detecting regions with similar textures based on variations in hue and intensity. More formally, the co-occurrence matrix tells us the joint probability of observing a pair of hue and intensity levels in each neighborhood. This information is then used to calculate texture measures such as homogeneity and correlation, which are incorporated into our Markov field model to improve aerial image segmentation. These characteristics make it easier to distinguish homogeneous regions, enhancing the quality of the segmentation.

D. Role of Contour Detectors

Contours play a fundamental role in the segmentation of aerial images. Precise delineation of regions of interest depends largely on edge detection. Several methods have been developed to accomplish this task [11], each with its own advantages and disadvantages.A single edge detector may be limited in its ability to capture the diversity of existing edges. This is why we use a combination of detectors in our approach, each bringing its own specific expertise to highlight certain types of contours to identify the boundaries between objects and structures present in the image.The information extracted by these edge detectors is incorporated into our Markov field energy function, which promotes edge coherence between pixels and, as a result, more robust and accurate segmentation.

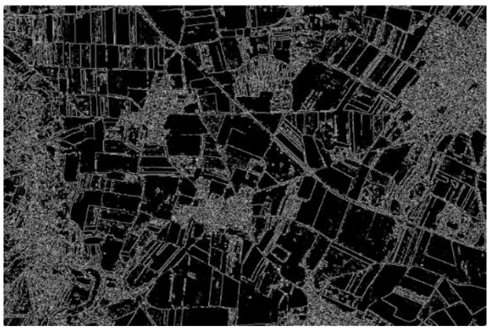

Fig 6. Edge Detection Result

III. METHODOLOGY

In this section, we describe in detail the methodology we have developed for the segmentation of aerial images using Markov fields with a multimodal energy function.

A. Multimodal approach to the Energy Function

Our segmentation approach is based on a multimodal energy function, designed to capture various key features of aerial imagery simultaneously. This energy function integrates color difference based on the CIEDE2000 metric, texture features, and detected edge information. The aim of this approach is to improve the consistency and accuracy of segmentation by taking advantage of several key attributes.

B. Combining Attributes in the Energy Function

- CIEDE2000 color difference: The CIEDE2000 metric is integrated into the energy function as a measure of pixel similarity. It encourages the grouping of pixels that share similar color characteristics, while taking subtle color nuances into account.
- Texture: Texture characteristics are extracted from aerial images and used to assess the textural coherence of regions. This component of the energy function distinguishes homogeneous regions from textured areas, contributing to more accurate segmentation.
- Contour detector: Detected contour information is incorporated to encourage contour consistency in segmentation. This component aims to ensure that the boundaries of the regions of interest are well defined.

C. Markov field model

The Markov field model is the underlying structure of our segmentation method. It is used to model the spatial relationships between pixels and to propagate information about whether pixels belong to a particular class. We use a conditional Markov field (CMF) model to describe the spatial dependency of pixels and attributes within the image. This allows us to efficiently exploit the multimodal information embedded in the energy function.Our Energy function incorporates color difference, texture and contour detector attributes:

The energy function E is defined as the sum of three terms:

$$E(I,S)=\alpha\, E_{color}(I,S) + \beta\, E_{texture}(I,S) + \lambda\, E_{contour}(I,S)$$

Where:

α , β ,λ are weighting coefficients to control the influence of each term of the function.

I represent the input image.

S is the map of segmentation labels, where each pixel is associated with a class (object or background).

Each term in the energy function is defined as follows:

- *CIEDE2000 Color Difference Term:*

E_{color} (I,S) measures the color difference between pixels in the same region (class) in the segmented image I_S using the CIEDE2000 metric. It encourages color consistency within each region:

$$E_{\mathrm{Color}}(\mathrm{I},\mathrm{S}) = \sum_{r}\sum_{p\in r}\Delta\mathrm{E00}(\mathrm{I_p}, \mu_r)$$

The average μr essentially represents the average color of region r in CIELab space. It is calculated by traversing all the pixels that belong to the region reconverting its color components (L, a, b) in CIELab space, summing them to obtain three sums: ΣL, Σa and Σb, then devising each sum by the number of pixels N in the region r to obtain the average components μr of the region r. To optimize processing, a region graph is constructed with the number of pixels N and the mean μr, which is updated each time a pixel is added to a region.

$\Delta E00$ (I_p , μ_r) is the CIEDE2000 color difference between pixel Ip and the average color of region r (μ_r). The lower ΔE00 is, the more similar the color of pixel Ip is to the average color μr of region r.

- *Texture term:*

$E_{texture}$(I, S) evaluates the texture in each segmented region. We will use texture measurements based on the co-occurrence matrix calculated from the variation of the Hue and intensity attributes of the pixel color in HSV space with respect to the average of the region and neighborhood to which it belongs, to promote the homogeneity of textures within each class:

$$E_{\text{texture}}(\mathrm{I},\mathrm{S}) = \sum_{r}\sum_{p\in r} 1 - \mathrm{H}(\mathrm{I_p}, \mu_r)$$

$H(I_p, \mu_r)$ is a measure of the homogeneity of the texture of pixel Ip with respect to the region μ_r to which it belongs, The higher H is, the more homogeneous the texture.the homogeneity measure from the co-occurrence matrix is already a normalized value between 0 and 1, where 0 represents minimum homogeneity (maximum variability) and 1 represents maximum homogeneity (no variability). This is why we subtracted the homogeneity value from 1 to minimize the Energy function the more homogeneous the region.

We will follow the steps below to calculate $H(I_p, \mu_r)$:

1. Calculate the co-occurrence matrix for the region r : For each pixel Ip in region r, examine the Hue and intensity attributes of the neighboring pixels (we'll use neighborhood 8) in region r. Create the co-occurrence matrix, which records the frequency of pairs for each attribute and is generally symmetrical.

2. Normalize the co-occurrence matrix: each element of the co-occurrence matrix is divided by the sum of all the elements of the matrix to normalize the values in the range 0 to 1. This step produces a co-occurrence probability matrix.

3. Calculate homogeneity: the standardized matrix is used to calculate homogeneity, which is a measure of the inverse of the variation in the attributes used.

The formula used to calculate the homogeneity $H(I_p,\mu_r)$ is as follows:

$$H(I_p,\mu_r)=\sum_{i,j} 1+|i-j|2P(i,j)$$

P(i,j) is the probability of co-occurrence of chromaticity's i and j in the normalized matrix.|i-j| is the difference between chromaticity i and j.4. Average homogeneity: Once the homogeneity has been calculated for each pixel Ip in region r, these values can be averaged to obtain an overall measure of the homogeneity of the texture in region r.This measure will be used as a component of our energy function to encourage texture consistency within each segmented region. The higher the homogeneity, the more uniform the texture is, and vice versa.

- Contour term:

$E_{contour}(I, S)$ encourages contour consistency, Firstly, we will use edge detectors to identify the edge locations in our image and then build an edge map where the marked pixels or regions correspond to the edge locations. This map will contain binary values (edge or non-edge).

The following function is defined:

$$E_{\text{Contour}}(\mathrm{I},\mathrm{S}) = \sum_{r}\sum_{pq\in r} D_{pq}.\,|\mathrm{S_p}, \mathrm{S_q}|$$

D_{pq} is a factor based on contour detection between pixels Ip and Iq. It is calculated by comparing the contour values of neighboring pixels p and q in the contour map. If pixels p and q are neighbors and one is on the contour while the other is not, this indicates a label discontinuity along the contour:

If pixel p is on the contour (high contour value) and pixel q is not on the contour (low contour value), or vice versa, then D_{pq} is defined as a high penalty factor, $D_{pq} = 1$ (to strongly penalize label discontinuity).If the two pixels p and q are both on the contour (or both outside the contour), it is defined as a low penalty factor, $D_{pq} = 0$ (so as not to penalize label consistency). The expression "$|S_p - S_q|$" is a term which measures in absolute value the difference in labels (S_p and S_q) of pixels p and q within the same region of the segmentation and which penalizes label discontinuities to encourage their coherence within each region. If "S_p" and "Sq" are the same (i.e. neighboring pixels have the same label), then "$|S_p - S_q|$" is zero. This means that there is no penalty for label consistency, as the labels are already the same. On the other hand, if "S_p" and "Sq" are different (i.e. neighboring pixels have different labels), then "$|S_p$ - Sq|" is greater than zero. This means that there is a penalty for label discontinuity within the same region. This penalty encourages the model to assign similar labels to neighboring pixels in the same region, thereby promoting the consistency of the segmentation. This energy model integrates the three attributes (color difference, texture, and contours) to promote the coherence of the segmentation regions by taking into account the visual and structural characteristics of the pixels. Segmentation is achieved by minimizing this energy function using the Iterated Conditional Modes (ICM) optimization algorithm.

- ICM algorithm for Segmentation Optimization

The segmentation is optimized using the Iterated Conditional Modes (ICM) algorithm. This is an efficient iterative algorithm that iterates through the set of pixels taking into account spatial dependencies and the multimodal energy function and seeks to find the best pixel label configuration that minimizes the energy function E(I,S) and corresponds to the most accurate segmentation[16].However, an iterative algorithm without a stopping condition could continue to iterate indefinitely. Introducing this stopping condition saves computation time and resources by stopping the algorithm once convergence criteria are satisfied.In our method we will use a combination of several of these conditions to ensure that the algorithm stops appropriately. More specifically, we will apply the global energy convergence criterion combined with the execution time to prevent the algorithm from running in an infinite loop.

Algorithm :

***** Input *****

S: Source image
α, β, λ: Ponderation parameters
ε: Convergence threshold

τ: Maximum execution time
** ***Initialization*** **
Read the source image S
Convert S to HSV space S_{HSV}
Convert S to Lab space S_{Lab}
Calculate the contour map
Compute Homogeneity and correlation for each pixel $x \in S$
Initialize the LabelMap with Labels $\{1,2,......,S_{High} x S_{Width}\}$
** ***Label Propagation*** **
For each pixel (x in S):
** *Neighborhood Label Update:* **
If P1 and P2 are Neighborhood Pixels
And $P1_{indH} = P2_{indH} = 1$ **Then**
P1Label = P2 Label = min (P2 Label, P2 Label)
** ***Energy Minimization*** **
For each pixel (x in S):
** *Compute Energy Function:* **
Calculate $E(I, S) = \alpha\, E_{Color}(I, S) + \beta\, E_{texture}(I, S) + \lambda\, E_{contour}(I, S)$
***Update Label:* **
Evaluate E(I, S) and update the label X_{Label}
***Convergence Check* **
While $\|E(I, S)_{New} - E(I, S)_{Old}\| \geq \varepsilon$ AND Execution time < τ:
For each pixel x **in** S:
***Update label based on energy minimization:* **
X_{Label} = argmin_Label E (I, S) for all possible labels
**Update Energy: **
$E(I, S)_{Old} = E(I, S)_{New}$
Output
Display the final segmented image

IV. RESULT

In this phase, the algorithm begins by reading the source image S. Subsequently, the conversion of the image S to the HSV and Lab color spaces is performed, providing a suitable representation for color and brightness analysis. The contour map is calculated to capture significant variations in the image. Simultaneously, measures of homogeneity and correlation are computed for each pixel, laying the foundation for the initial label assignment.the label propagation phase is initiated to establish initial relationships between neighboring pixels. For each pixel x in the source image S, a neighborhood analysis is conducted to examine adjacent pixels, namely P1 and P2. If both exhibit homogeneity ($P1_{indH} = P2_{indH} = 1$), their labels are adjusted to ensure coherence. This step aims to create an initial label assignment that considers the homogeneity characteristics within local pixel neighborhoods, setting the groundwork for subsequent energy minimization and label refinement.

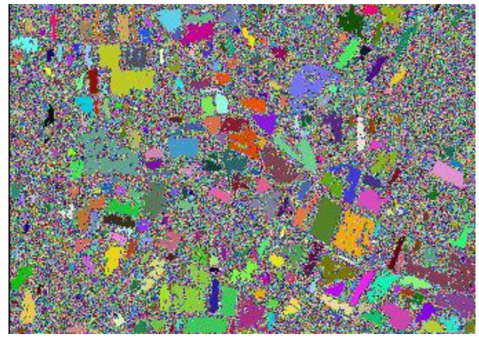

Fig 7. Class and Label assignment after Neighborhood Label Update.

In this phase, the system's energy is minimized for each pixel x. The energy function E(I,S) is calculated by combining contributions from CIEDE2000 color difference, texture, and contours. This energy is used to update labels, promoting pixel coherence within the context of the entire image.
The convergence check loop is introduced to iterate through label updates until satisfactory convergence is achieved or the specified maximum execution time (τ) is exceeded. In each iteration, labels are updated using the ICM approach, where each pixel adjusts its label to minimize local energy. This step continues until the energy difference between consecutive iterations falls below a threshold ε, indicating satisfactory convergence.

Fig 8. Final Labeling Result.

Finally, the algorithm leads to the presentation of the final labeling result, displaying the segmented image. The optimized labels obtained after the algorithm's convergence reflect the successful segmentation of the original image based on color, texture, and contour criteria.

Fig 9. segmented image.

V. CONCLUSION

The image segmentation approach based on Markov field methodology (MRF) and exploiting the attributes of color difference, texture and edge detection was subjected to an exhaustive evaluation. The results obtained demonstrate the robustness of our method in accurately delineating the contours of complex objects within images.The CIEDE2000 color difference measurement was particularly effective at capturing subtle variations in color, ensuring accurate segmentation even under changing lighting conditions. The incorporation of texture information has enhanced the method's ability to discriminate between homogeneous but textured regions, improving segment consistency. At the same time, the use of edge detectors, such as the Canny operator, has made it possible to highlight the boundaries between objects, improving the sharpness and overall accuracy of the segmentation.To quantitatively evaluate the performance of our approach, we used commonly used metrics such as precision, recall and F-measure. The results demonstrated competitive performance.

with existing methods, highlighting the ability of our model to produce segmentations faithful to the real contours of objects in a variety of images.In addition, in-depth visual analyses have been carried out, highlighting the ability of our method to handle complex cases such as the presence of fine structures, objects with blurred edges, and significant texture variations. These qualitative observations confirm the relevance of our approach in various applications, from computer vision to medical image analysis.In conclusion, the results obtained support the validity and effectiveness of our Markov field-based image segmentation approach, demonstrating its potential for a variety of applications requiring accurate and robust segmentation. Ongoing improvements and future extensions to this methodology promise to further enhance its versatility and applicability in a variety of contexts.

REFERENCES

[1] S. Y. Chen, H. Tong, et C. Cattani, « Markov Models for Image Labeling », *Mathematical Problems in Engineering*, vol. 2012, p. e814356, août 2011, doi: 10.1155/2012/814356.

[2] Z. Kato, « Markov Random Fields in Image Segmentation », *Foundations and Trends® in Signal Processing*, vol. 5, nº 1-2, Art. nº 1-2, 2011, doi: 10.1561/2000000035.

[3] V. V. Mottl, A. B. Blinov, A. V. Kopylov, et A. A. Kostin, « Optimization Techniques on Pixel Neighborhood Graphs for Image Processing », in *Graph Based Representations in Pattern Recognition*, J.-M. Jolion et W. G. Kropatsch, Éd., in Computing Supplement. Vienna: Springer, 1998, p. 135-145. doi: 10.1007/978-3-7091-6487-7_14.

[4] H. Derin et H. Elliott, « Modeling and segmentation of noisy and textured images using gibbs random fields », *IEEE Trans Pattern Anal Mach Intell*, vol. 9, nº 1, p. 39-55, janv. 1987, doi: 10.1109/tpami.1987.4767871.

[5] S. Geman et D. Geman, « Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images », *IEEE Transactions on pattern analysis and machine intelligence*, nº 6, Art. nº 6, 1984.

[6] P. Clifford et J. M. Hammersley, « Markov fields on finite graphs and lattices », 1971, https://ora.ox.ac.uk/objects/uuid:4ea849da-1511-4578-bb88-6a8d02f457a6

[7] S. Dachian et B. Nahapetian, « On Gibbsianness of Random Fields ». arXiv, 12 septembre 2007. doi: 10.48550/arXiv.math/0609688.

[8] R. He, K. Xiao, M. Pointer, M. Melgosa, et Y. Bressler, « Optimizing Parametric Factors in CIELAB and CIEDE2000 Color-Difference Formulas for 3D-Printed Spherical Objects », *Materials*, vol. 15, nº 12, Art. nº 12, janv. 2022, doi: 10.3390/ma15124055.

[9] M. Gomez-Polo, M. Portillo, M. Luengo, P. Vicente, P. Galindo, et M. María, « A comparison of the CIELab and CIEDE2000 color difference formulas », *The Journal of prosthetic dentistry*, vol. 115, sept. 2015, doi: 10.1016/j.prosdent.2015.07.001.

[10] R. M. Haralick, K. Shanmugam, et I. Dinstein, « Textural Features for Image Classification », *IEEE Transactions on Systems, Man, and Cybernetics*, vol. SMC-3, nº 6, p. 610-621, nov. 1973, doi: 10.1109/TSMC.1973.4309314.

[11] R. Sun *et al.*, « Survey of Image Edge Detection », *Frontiers in Signal Processing*, vol. 2, 2022, https://www.frontiersin.org/articles/10.3389/frsip.2022.826967

[12] F. Mokhtarian et F. Mohanna, « Performance evaluation of corner detectors using consistency and accuracy measures », *Computer Vision and Image Understanding*, vol. 102, nº 1, p. 81-94, avr. 2006, doi: 10.1016/j.cviu.2005.11.001.

[13] X. Wang, « Laplacian Operator-Based Edge Detectors », *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, nº 5, p. 886-890, mai 2007, doi: 10.1109/TPAMI.2007.1027.

[14] L. Chandrasekar et G. Durga, « Implementation of Hough Transform for image processing applications », in *2014 International Conference on Communication and Signal Processing*, avr. 2014, p. 843-847. doi: 10.1109/ICCSP.2014.6949962.

[15] W. McIlhagga, « The Canny Edge Detector Revisited », *Int J Comput Vis*, vol. 91, nº 3, p. 251-261, févr. 2011, doi: 10.1007/s11263-010-0392-0.

[16] J. Sublime, Y. Bennani, et A. Cornuéjols, « A Compactness-based Iterated Conditional Modes Algorithm For Very High Resolution Satellite Images Segmentation », janv. 2015.