Graph matching versus bag of graph: a comparative study for lettrines recognition

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***Abstract*—This paper proposes a comparison of three classification methods of graphical historical images. Historical image datasets are becoming bigger and bigger, and the use of classical computer vision techniques is not sufficient to deal with these large repositories. In the context of this paper, we propose to compare three methods by applying graph matching techniques on a dataset already used in many papers. The first one is based on a statistical approach, the second one on a graph-based classification, and finally the third one is an hybrid approach relying on the specificities of the two previous one. For this last method, we propose here to adapt it to this specific dataset. Some results are proposed and commented, what shows the superiority of the hybrid approach.**

***Keywords*—Lettrine, Historical graphical documents, graph-based representation, indexing**

I. Introduction and context

With the improvement of printing technology since the 15th century, a huge amount of printed documents have been published and distributed. Since that time, many of the books have been falling into decay and have been degraded by the time. Due to their intensive manipulation, the physical objects, *i.e.* books themselves, are in potential danger of extinction, as well as our cultural heritage. Therefore, there are a lot of attempts to keep, organize and restore ancient printed documents, in order to preserve these documents and their contents. As a consequence, many digitizing processes can be observed worldwide in many institutions, in order to protect physical objects from human degradation and in order to share historical information. However, even if digital era offers many opportunities, the digitized documents are not sufficient by themselves if one wants to offer the possibility to retrieve, navigate, and extract information from documents. Some dedicated tools using some document analysis and indexing process are needed.

Driven by rapidly changing amounts of digitized historical document, some specific pattern recognition systems have been defined. Indeed historical's document images, such as lettrines (decorative capital letters), are particularly hard to process into recognition scheme since they contain a lot of information (like texture, decorated background, letters). Figure 1 illustrates some samples of lettrines. One can remark that each image is a mixture of components such that the letter in the one hand and the background pattern on the other hand. In addition, some degradation linked to the state of original paper and the digitization can be observed. To deal with this kind of properties, pattern recognition systems require specific techniques which take into account these characteristics.

Many works tended to index and to search for similar complex historical images [1], and generally the results related to pattern recognition can be broadly divided into statistical and structural methods [2]. In the former, the document is represented by a feature vector [3], [4], and in the latter, a data structure (e.g. graphs or trees) are used to describe objects and their relationships in the document [5], [6].

Fig. 1. Examples of lettrine images

Finding a proper representation of objects is a key issue in pattern recognition and document analysis. Common ways of object representation generally rely on the use of statistical pattern recognition techniques (like features vectors) to summarize the radiometric content of an image on one hand, or on the use of structural pattern recognition approaches to summarize the topological organization of image's content (trees, graphs, ...) on the other hand. Most of the recognition systems are limited to work with a statistical representation, mainly due to the need of computing distances between documents (feature vectors) or because of the necessity of finding a representative of a cluster of documents. When a numerical feature vector is used to represent the document, the structural information is generally discarded while the structural representation allwos to keep it. Structural representations are generally more powerful in terms of their representational abilities [2]. In a general comparison of these two approaches, we can observe that:

- \+ Features vectors have a low computational complexity and many algorithms are available
- \- Features vectors have a limited representational power and the dimensionality is fixed, (i.e. all the images are reduced to the same quantity of information)

- \+ Graphs have a high representational power (mainly linked to their capacity to represent topological relations) and a lot of flexibility as there are no initial limitations on graph size

- Graph matching techniques generally have a high computational complexity

Since we deal with complex images (lettrines), the structural approaches seem to be more suitable for the representation task. Graph-based representation means to be able to compute a distance between two graphs. This can be done using some graph kernels techniques to reduce a graph to a feature vector or by using some graph matching techniques to compare the topology of these two graphs. In the specific case of lettrines, different works aimed at representing lettrines with graphs and computing some distances based on matching techniques [7], [5]. A new idea, proposed in [8], aims at mixing the power of structural comparison techniques (graph matching techniques) with the bag of words model. We propose a comparison between these two recent works based on graphs in this paper.

II. Methods compared in this study

Based on graph-based representation of historical images, this paper proposes to compare three recent approaches using the same distance between graph. The first method uses a graph matching technique that compares the structural information of graphs, second one uses a bag of word model to statistically compare images, while the last one is hybrid as it relies on the use of Bag of Graphs (BoG), which is an adaptation of the Bag-of-Words model to graph domain [8].

The choice of these three methods relies on the fact that they use the Heterogeneous Euclidean Overlap Metric (HEOM) distance defined in [9] to compute a distance between two graphs. This metric has proved its reliability for image recognition[5], [8]. Moreover, this distance between graphs keeps some information related to the structure of graphs by taking into account:

- the attribute of the node n_i: α_i
- the degree of n_i: $\theta(n_i)$
- the degrees set of the nodes adjacent to n_i: $\{\theta(n_i)\}_{\forall ij \in E}$
- the attributes set of the incident edges to n_i : $\{\beta_{ij}\}_{\forall ij \in E}$

Let i and j be the features vectors respectively linked to the i^{th} and the j^{th} node. A node signature distance based on the HEOM which handles numeric and symbolic attributes can be defined by the function $HEOM(i, j)$:

$$HEOM(i,j) = \sqrt{\sum_{\alpha=0}^{A} \delta(i_a, j_a)^2} \tag{1}$$

where α refers to one attributes of A and $\delta(i_a, j_a)$ is defined as:

$$\delta(i_a, j_a) = \begin{cases} 1 & \text{if} \quad i_a \, or \, j_a \, is \, missing \\ Overlap(i_a, j_a) & \text{if} \quad \alpha \, is \, symbolic \\ rn\_diff_a(i_a, j_a) & \text{if} \quad \alpha \, is \, numeric \end{cases} \tag{2}$$

Starting from this distance, it then becomes possible to compute a distance between nodes of graph, and a graph matching technique or a statistical classification process can be applied to compare images. We selected three methods that complement each other to evaluate the performance of structural and statistical approaches. The first one, which is structural [9] is a graph-based approach, while the second one, which is statistic, mimics the bag of visual words models [8]. Finally, the third one is an hybrid one which uses the HEOM distance in a Bag of Visual Words model.

A. *Graph-based approach*

Classically, graph-based approaches rely on the use of matching techniques to check if two graphs are similar, i.e. they share the same structural representation. Many works were done in this field to find similarities between graphs with different techniques. We can cite some recent works that used a vectorial representation for the indexing of structural Informations [10], that extracted some features from graph to summarize their content with a fuzzy multilevel graph embedding [11] or a family of methods that tried to evaluate the distance between graphs by minimizing edit distance. This last means counting the least cost of edit operations needed to make two graphs isomorphic. A standard set of edit operations is given by insertions, deletions and substitutions. These edit operations are applied on both edges and nodes. In addition, a certain cost is associated with each of these operations. Obviously, for every pair of graphs A and B there exists different sequences of edit operations transforming A into B. However, the computation of the edit distance between two graphs involves not only finding a sequence of edit operations to transform one graph to the other, but also finding such a sequence that possesses the minimum total cost. Formally, The graph edit distance between two graphs A and B is given by:

$$d(A, B) = \min_{(e1,..,ek) \in \gamma(A,B)} \sum_{i=1}^{k} c(e_i) \tag{3}$$

where $\gamma(A, B)$ denotes the sequences of edit operations transforming A into B and $c(e_i)$ denotes the cost of the edit operation e_i. In order to compute an optimal graph edit distance, several techniques have been proposed. In this paper, we consider an improvement of the approximation of graph edit distance based on [12], [9] using the HEOM.

B. *Bag of visual words*

The second method evaluated in this paper is described in [7] and relies on a widespread approach of the literature: the bag of words (BoW) model [13], [14]. This model [15] was originally designed for text classification and retrieval. Its main idea is to represent each text by a vector that counts the occurrences of words in the document. The similarity between two texts is evaluated based on the similarity of their words distribution. The BoW model has been used in different domains and adapted to the natural image analysis with the introduction of Bag of Visual Words (BoVW) [16], [17]. We also adapted it to historical images in [18] where visual words where extracted using $3 * 3$ patterns defined in [19].

Based on this principle, this approach combines the use of the Zipf law and the use of bag of patterns, in order to identify the most important $3 * 3$ patterns for each image. In fact, each image is described by a vector that contains the list of most interesting patterns. This selection however involves different sizes of vector, and different features in vectors. A similarity measure between images (*ie.* vectors) was defined to compare images. This measure between two vectors (v_1 and v_2) relies on a series of three values.

1) Length Ratio: R_L
2) Similarity Ratio: R_S
3) Pattern Distance: D_{Patt}

The two first ratios indicate the similarity between two vectors. R_L and R_S have a value $\in [0;1]$, with 0 corresponding to dissimilar vectors, while 1 indicates a perfect similarity between them. On the other hand, the pattern distance correspond to an euclidean distance. This means that the smaller the distance is, the closer the vectors are (and vice-versa). These three values are combined into a global similarity measure. Considering two images i_1 and i_2, the measure is defined as:

$$Sim_{i_1,i_2} = (1 - (R_L * R_S)) * D_{Patt})$$

C. Hybrid approach

Finally, the last approach presented is hybrid since it relies on the use of Bag of Graphs (BoG), which is an adaptation of the Bag-of-Words model to graph domain. In this approach, the local structures of a graph are described by node signatures and each graph is represented as a bag of node signatures.The graph matching problem is then reduced to the problem of computing the similarity between feature vectors like in the classical bag of words method. We decided to use the HEOM distance to compare nodes as it allows keeping structural information of graph. Moreover, we used the euclidean distance to compare two feature vectors, but any other distance (like the Manhattan or the Earth Mover's distance) could be used in this last step.

The BoG approach is a two-steps process that performs graph classification and graph retrieval. First, a learning phase generates the codebook used for the bag representations, and in the second phase, the graph classification process consists in computing an euclidean distance between a query and all the graphs in the database as they are reduced to a feature vector. The class of the most similar histogram allows deducing the class of the query. To generate the codebook, we take all the nodes of graphs with their local features (see below for details) and we input them in a clustering algorithm to compute some nodes' prototypes.

The local features of a vertice used for the bag representation relies on features associated to the node itself, but also to its neighborhood. More formally, let $G = (V, E)$ be a graph composed of a set of vertices V and a set of edges E, A_V the set of attributes (numeric or symbolic) related to the vertices, A_E the attributes (numeric or symbolic) related to the edges and D_i the degree of vertice v_i. The node signature NoS of v_i corresponds to the list of these information and can be defined as follows:

$$NoS(v_i) = A_{V_i} \,;\, D_i \,;\, A_{E_iD} \tag{4}$$

where A_{Ei_D} corresponds to the set of attributes of edges linked to the node ($A_{E_{i1}} \,;\, \ldots \,;\, A_{E_{iD}}$). This set is sorted in order of increasing values to ensure a consistency when comparing two node signatures.

We also assume that graphs correspond to a segmentation process, and that each node corresponds to a region in the image. We thus propose to use the following features for node's description: X and Y coordinates, area and eccentricity. To describe edges with the following set of features: the distance between region centroids, the degree of the neighbor node and the orientation of the edge. Finally, we apply the Mean Shift algorithm [20] to create the codebook in the learning phase. The use of an unsupervised clustering method, like Mean Shift, simplifies the process of building the dictionary. Starting from this codebook, each node of the graphs is associated to a cluster, and each graph is then described by an histogram of nodes' prototypes.

Now that we have presented the methods, we present the dataset used to compare these approaches and to discuss on the performances and the differences between them.

III. EXPERIMENTAL RESULTS

A. Lettrines in details

Lettrines are particularly difficult images (images degraded by time in black and white) and many works tried to recognize them using some statistical and structural approaches [21], [7]. We decided to use the dataset of these papers to compare these methods and to propose an objective evaluation. It contains more than 300 images coming from the *Centre dEtudes Superieur de la Renaissance* of Tours, France. Images from this database have been labeled by experts who indicated the style of the lettrine. The three main styles are presented in figure 2.

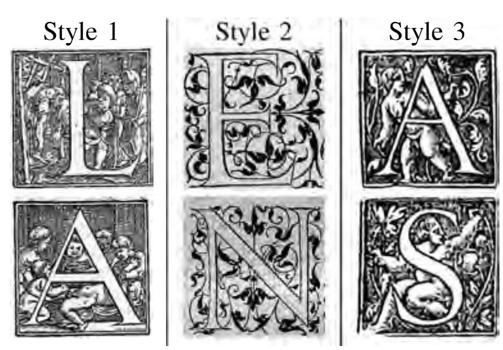
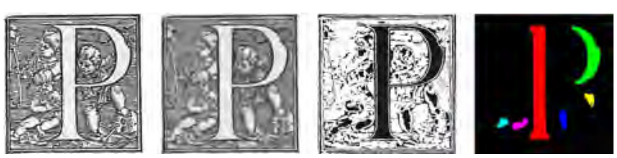


Fig. 2. Examples of lettrines for each style present in the database used in [21]. Style 1 correspond to lettrines composed of hashed background, style 2 contains lettrines with white and decorative background, and style 3 lettrine with a black background with white dot

As one can see on figure 1, lettrines are made up of two principal elements: the letter and the background. These elements are used by historians to retrieve similar lettrines in order to identify the printer and the period. This paper proposes to compare different methods to identify the style of the background. In order to be able to identify the style with graph-based approaches, we extracted regions of interest from lettrines and described them with graphs. Our aim is to extract some meaningful region that correspond to pure geometrical component. For this, in [19], authors propose a decomposition model which splits an image into three components: the first one, u, containing the structure of the image (see Figure 3(b) for an example), a second one, v, the texture, and the third one, w, the noise. For better comprehension of differents spaces, see [22]. We are particularly interested by the first one which capture region with low variation of greylevels, that represent the meaningful regions. From this image, we apply a Zipf law, a three steps process, to extract regions of interest:

- Simplification of image applying a 3-means on grey level histogram to reduce number of patterns (the choice of three can be explained by the fact that images are composed of three elements : background, foreground, motif)
- Seek for patterns the size of which is 3 by 3 to obtain their frequency and their rank (that can be resume to a count of each pattern that permit to know their frequency and their rank)
- Classification of patterns according to the evolution law of the frequency compared to their rank. From the precedent step, three straight lines are computed to estimate the main parameters of Zipf laws that interfere. The first one corresponds to the most frequent patterns (shapes of image) and an example of result is presented in Figure. 3(c)



(a) (b) (c) (d)

Fig. 3. Example of an image and representation of different treatments: a) Original image; b) Region with low variation of greylevels; c) Shapes segmented using Zipf law (in black); d) Six larger connected component

Once shapes have been extracted, one can seek connected components of binarized image. When observing all the connected components in Figure 3(c), we can see that the most important shapes have particular characteristics (based on size, location, center of mass and exccentricity). A selection of connected components in accordance with these parameters permit to obtain region of interest of drop caps. An exmaple of extracted connected components can be seen in Figure 3(d).

From all these extracted shapes, we build a graph where nodes correspond to region of interest. Each node is described by a quadruplet of information which contain the coordinate of the center of mass, area and eccentricity of each shape. An illustration of this last process is presented in figure 4.

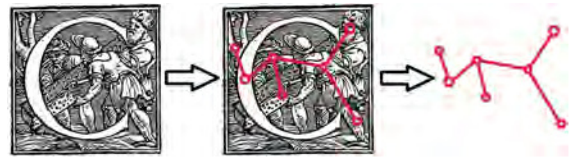


Fig. 4. An example of graph extracted after the segmentation process

B. Evaluation protocol

As presented before, the methods presented rely on a training phase and a recognition phase. For this evaluation, We used 10 images by style (ie. class) in the learning step (13% of all database images), and the rest for the recognition step. For all images, the distance between the image and all the others of the database are computed using the HEOM metric for methods 1 and 3, while the ”Pattern metric” was used for the second work. We then used a k-nearest neighbour (k-NN) classifier to class each image in a style. The obtained results are summarized in table I.

C. Results and discussions

We computed all these methods on the dataset and we obtain the results presented in table I. These results correspond to the accuracy of our system to identify the good style. It can be seen as the Precision of our system with only 1 result returned for each query (Precision@1).

Method	Style 1	Style 2	Style 3	Total
Graph matching	75,9%	46,7%	64,2%	71%
Bag of Visual Patterns	73,8%	60%	64,2%	70,3%
Bag of graphs	87,9%	0%	81,6%	81,5%

TABLE I. ACCURACY COMPARISON BETWEEN STATISTICAL AND STRUCTURAL APPROACHES

First of all, we can see that the graph matching and the bag of visual patterns provided very similar results and that it is quite difficult to recognize more than 70% of the dataset with previous works. We can particularly see that the statistical-based approach got better results with the class ”Style 2”. This can be explained by the fact that this class is mainly composed of lettrines with a white background, small flowers and the letter. Statistically, it is easier to retrieve images with the same proportion of patterns, while the regions extracted and put in the graphs are not always the same. One solution that could be considered will be to compute more features for the regions and to add them into the graph matching system. However, adding more complex features will imply higher computation time and it could be difficult to retrieve similar regions that are not only composed of white (regions composed of textures).

Regarding the bag of graph approach, which corresponds to the most recent work, it seems to globally present better results. The main drawback of this approach is that it relies on the mean-shift algorithm to define the node clusters in the learning phase. As in this work we limited to 10% this stage, we can see that the system is not able to correctly define some prototypes for all the classes (style 2 is never recognized). At the opposite, the results obtained for style 1 and 3 are the best of this evaluation. Finally, we can notice that the last method mixes some statistical and structural approaches, and that this combination of information clearly enhance the results by 10% .

A perspective of this work is to evaluate the difference between these approaches regarding the algorithmic complexity, and thus its computation time. Actually, the dataset involved is quite limited (obtaining a larger annotated dataset of historical document is quite difficult) and all these methods computed the results in an equivalent duration (about 15 seconds to classify all the dataset). This similarity is mainly due to the fact that lettrines are represented with small graphs (15 nodes in general). In that configuration, computing the matching between all graphs is quite similar to the computation of a clustering algorithm and the computation of histogram distances between images. However, we have to notice that this computation time do not take into account the pre-processing techniques which consisted in the graph generation in the structural of hybrid approach, while the statistical approach (Bag of Visual Patterns) starts from the original images.

IV. Conclusion and perspectives

In this paper we propose a comparative study of three methods applied on historical images: a statistical, a structural and an hybrid approach. We used a well-know dataset of historical images to compare these methods and we can conclude that the hybrid one take advantage of this mix and obtain better results. The next step of this work will be to extend the dataset in order to compare these approaches not only on historical documents but more generally to documents. Another promising issue could be to propose a combination of these classification process as each classification technique has its own errors different from the others.

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References

[1] D. Doermann, K. Tombre *et al.*, *Handbook of Document Image Processing and Recognition*, K. T. David Doermann, Ed. Springer-Verlag London, 2014.

[2] H. Bunke, S. Gnter, and X. Jiang, "Towards bridging the gap between statistical and structural pattern recognition: Two new concepts in graph matching," in *Advances in Pattern Recognition ICAPR 2001*, ser. LNCS, S. Singh, N. Murshed, and W. Kropatsch, Eds. Springer Berlin Heidelberg, 2001, vol. 2013, pp. 1–11. [Online]. Available: http://dx.doi.org/10.1007/3-540-44732-6_1

[3] M. Mehri, P. Gomez-Krämer, P. Héroux, A. Boucher, and R. Mullot, "Texture feature evaluation for segmentation of historical document images," in *Proceedings of the 2nd HIP*. ACM, 2013, pp. 102–109.

[4] J. Almazán, A. Gordo, A. Fornés, and E. Valveny, "Word spotting and recognition with embedded attributes," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 36, no. 12, pp. 2552–2566, 2014. [Online]. Available: http://doi.ieeecomputersociety.org/10.1109/TPAMI.2014.2339814

[5] S. Jouili and S. Tabbone, "Hypergraph-based image retrieval for graph-based representation," *Pattern Recognition*, vol. 45, no. 11, pp. 4054 – 4068, 2012. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0031320312001963

[6] R. Raveaux, J. Burie, and J. Ogier, "Structured representations in a content based image retrieval context," *J. Visual Communication and Image Representation*, vol. 24, no. 8, pp. 1252–1268, 2013. [Online]. Available: http://dx.doi.org/10.1016/j.jvcir.2013.08.010

[7] M. Coustaty and J. Ogier, "Discrimination of old document images using their style," in *ICDAR 2011, Beijing, China, September 18-21, 2011*. IEEE Computer Society, 2011, pp. 389–393. [Online]. Available: http://dx.doi.org/10.1109/ICDAR.2011.86

[8] F. B. Silva, S. Tabbone, and R. da Silva Torres, "Bog: A new approach for graph matching," in *22nd ICPR 2014, Stockholm, Sweden, August 24-28, 2014*. IEEE, 2014, pp. 82–87. [Online]. Available: http://dx.doi.org/10.1109/ICPR.2014.24

[9] S. Jouili, M. Coustaty, S. Tabbone, and J. Ogier, "NAVIDOMASS: structural-based approaches towards handling historical documents," in *20th ICPR 2010, Istanbul, Turkey, 23-26 August 2010*. IEEE Computer Society, 2010, pp. 946–949. [Online]. Available: http://dx.doi.org/10.1109/ICPR.2010.237

[10] N. Sidere, P. Héroux, and J. Ramel, "A vectorial representation for the indexation of structural informations," in *Joint IAPR International Workshop, SSPR & SPR, USA, December 4-6, 2008. Proceedings*, ser. LNCS, vol. 5342. Springer, 2008, pp. 45–54. [Online]. Available: http://dx.doi.org/10.1007/978-3-540-89689-0_9

[11] M. M. Luqman, J.-Y. Ramel, J. Llads, and T. Brouard, "Fuzzy multilevel graph embedding," *Pattern Recognition*, vol. 46, no. 2, pp. 551 – 565, 2013. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0031320312003470

[12] S. Jouili and S. Tabbone, "Graph matching based on node signatures," in *GbRPR 2009, Venice, Italy, May 26-28, 2009. Proceedings*, ser. LNCS, A. Torsello, F. Escolano, and L. Brun, Eds., vol. 5534. Springer, 2009, pp. 154–163. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-02124-4_16

[13] R. Datta, D. Joshi, J. Li, and J. Z. Wang, "Image retrieval: Ideas, influences, and trends of the new age," *ACM Comput. Surv.*, vol. 40, no. 2, pp. 5:1–5:60, May 2008. [Online]. Available: http://doi.acm.org/10.1145/1348246.1348248

[14] J. Sivic and A. Zisserman, "Efficient visual search of videos cast as text retrieval," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 31, no. 4, pp. 591–606, April 2009.

[15] R. A. Baeza-Yates and B. Ribeiro-Neto, *Modern Information Retrieval*. Boston, MA, USA: Addison-Wesley Longman Publishing Co., Inc., 1999.

[16] J. Sivic, B. Russell, A. Efros, A. Zisserman, and W. Freeman, "Discovering objects and their location in images," in *Tenth IEEE ICCV 2005*, vol. 1, Oct 2005, pp. 370–377 Vol. 1.

[17] N. Nguyen, M. Coustaty, and J. Ogier, "Multi-modal and cross-modal for lecture videos retrieval," in *22nd ICPR 2014, Stockholm, Sweden, August 24-28, 2014*. IEEE, 2014, pp. 2667–2672. [Online]. Available: http://dx.doi.org/10.1109/ICPR.2014.461

[18] T. T. H. Nguyen, M. Coustaty, and J. Ogier, "Bags of strokes based approach for classification and indexing of drop caps," in *ICDAR 2011, Beijing, China, September 18-21, 2011*. IEEE Computer Society, 2011, pp. 349–353. [Online]. Available: http://dx.doi.org/10.1109/ICDAR.2011.78

[19] M. Coustaty, R. Pareti, N. Vincent, and J. Ogier, "Towards historical document indexing: extraction of drop cap letters," *IJDAR*, vol. 14, no. 3, pp. 243–254, 2011. [Online]. Available: http://dx.doi.org/10.1007/s10032-011-0152-x

[20] D. Comaniciu and P. Meer, "Mean shift: a robust approach toward feature space analysis," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 24, no. 5, pp. 603–619, May 2002.

[21] R. Pareti and N. Vincent, "Ancient initial letters indexing," in *18th (ICPR 2006), 20-24 August 2006, Hong Kong, China*. IEEE Computer Society, 2006, pp. 756–759. [Online]. Available: http://dx.doi.org/10.1109/ICPR.2006.272

[22] J.-F. Aujol, G. Gilboa, T. Chan, and S. Osher, "Structure-texture image decomposition - modeling, algorithms, and parameter selection," *International Journal of Computer Vision*, vol. 67, no. 1, pp. 111–136, 2006. [Online]. Available: http://dx.doi.org/10.1007/s11263-006-4331-z

[23] *ICDAR 2011, Beijing, China, September 18-21*. IEEE Computer Society, 2011. [Online]. Available: http://ieeexplore.ieee.org/xpl/mostRecentIssue.jsp?punumber=6065245

[24] *22nd ICPR 2014, Stockholm, Sweden, August 24-28, 2014*. IEEE, 2014. [Online]. Available: http://ieeexplore.ieee.org/xpl/mostRecentIssue.jsp?punumber=6966883