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A TaLISMAN: Automatic Text and LIne Segmentation of historical MANuscripts

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Abstract

Historical and artistic handwritten books are valuable cultural heritage (CH) items, as they provide information about tangible and intangible cultural aspects from the past. Massive digitization projects have made these kind of data available to a world-wide population, and pose real challenges for automatic processing. In this scenario, document layout analysis plays a significant role, being a fundamental step of any document image understanding system. In this paper, we present a completely automatic algorithm to perform a robust text segmentation *of old handwritten manuscripts on a per-book basis, and we show how to exploit this outcome to find two layout elements, i.e.,* text blocks *and* text lines*. Our proposed technique have been evaluated on a large and heterogeneous corpus content, and our experimental results demonstrate that this approach is efficient and reliable, even when applied to very noisy and damaged books.*

Categories and Subject Descriptors (according to ACM CCS): I.3.0 [Computer Graphics]: General— I.3.3 [Computer Graphics]: Picture/Image Generation—Digitizing and scanning I.3.6 [Computer Graphics]: Methodology and Techniques— I.3.8 [Computer Graphics]: Applications—

1. Introduction

Massive digitization projects have made large collections of historic books and manuscripts available to a world-wide population interested in Cultural Heritage (CH). Digital access has made it possible for many people to use these valuable documents without the damage associated with physical handling. Beyond “touchless" access, digital formats offer the potential to index and search across large collections. To prepare rich metadata for indexing however there is a need for automatic tools that can analyze the structure and content of these books and manuscripts.

The analysis of modern printed materials has been well studied. However, the analysis of very old hand-prepared manuscripts remains problematic. Very old works suffer from a wide range of issues associated with wear and deterioration including smudges, stains, fading, ink bleed-through, scratches, holes, and creases. Further, hand-prepared manuscripts do not have standardized style or logical structure. Handwritten characters can have unusual or varying shapes. Ornamentation has often been added. Illustrations appear in varying locations, and often characters are embellished. Different types of annotations, written in different hands with different materials, have been added in the margins through the years. To our knowledge no reliable and completely automatic techniques for extracting and classifying the illustrations, text and annotations from old hand-prepared manuscripts have been developed.

In computer vision, document layout analysis splits documents into structural elements that can be labeled by class – such as text blocks and text lines. Extracting particular textual fields or blocks can assist scholars in paleographic analysis for the determination of the geographic and temporal origin of a manuscript. Further, identifying individual elements can facilitate automatic or semi-automatic text transcription to enable ASCII-based textual queries. Common tasks such as word-spotting (e.g., Fischer et al. [FKFB12]) or handwriting recognition are also assisted by layout analysis.

We present here an automatic, parameter-free framework for layout analysis of very old handwritten manuscripts. In particular we focus on the extraction of the following layout entities: text regions, rectangular text blocks and text lines. We rely on the estimation of the average text leading value (i.e., inter-line spacing) for all the pages in the

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book [PYR13], and on a class of text recognition methods [GSD11a, PYR14] that use Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel to classify sparse local image features, namely Scale- Invariant Feature Transform (SIFT). For each member of a sparse set of text feature positions, we extract neighbor points and a corresponding radius of influence. We use these to produce a dense segmentation of text regions. We then extract main rectangular text blocks, and, for each block, we find a text line segmentation by applying a Projection Profile technique [LSZT07, PYR14]. Here we list the major contributions of the proposed approach.

Page voting framework. We present a framework to select the most representative pages from a book to use to train a text feature vector classifier. This increases the probability of having a training set with well distributed feature vectors between the *text* and *non-text* classes. For each single page, the voting depends both on its hue histogram, and on the likelihood of its text leading value, given the corresponding per-book statistical text leading distribution.

Automatic coarse text segmentation. We improve the operator presented by Pintus et al. [PYR14] to perform automatic coarse text segmentation. We exploit their frequency based descriptor, which compares the average text leading value with the local spatial frequency at different window sizes. We also consider the amplitude of the predominant Fourier coefficients as a measure of the local text likelihood.

Automatic per-book basis text segmentation. On a per book basis, we perform a classification on a set of image features to obtain a sparse text segmentation of the book. We present a pipeline to convert this sparse representation into a dense separation between *text* and *non-text* pixel regions. We show how to exploit this outcome to find two layout elements, i.e., text blocks and text lines.

Evaluation. We extensively test and evaluate our document layout analysis pipeline with a large and heterogeneous corpus content, that includes different writing styles, image resolutions, levels of conservation, noise and amount of illumination and ornamentation. We provide a precision/recall analysis to quantitatively assess the quality of the proposed algorithm.

2. Related work

Layout analysis is a well-known and established topic among the Computer Vision techniques applied to document structure retrieval. Substantial work has been published including character and word spotting [YM12], layout segmentation [GBC09], ancient handwritten document classification [LGPH08], and extraction of text lines [JL12]. The literature in this area has been surveyed in Nagy's [Nag00] seminal work, as well as in recent reviews [LSZT07]. Here we discuss only the state-of-the-art techniques closely related to ours.

Efficient algorithms exist to cope with modern machine-printed documents or historical documents from the hand-press period, and to solve the traditional problems of layout analysis, such as document classification [CB07], text regions/blocks identification [WPH02], or segmentation of text lines [KC10]. However, the demand for and the complexity of the analysis of old manuscripts requires the development of new, more robust methods [AD07].

Common state-of-the-art approaches are based on image binarization and a morphological analysis of the page image [GBC11, BvKS*07]. Ramel et al. [RLDB07] exploit the generation of a connected component map within a semi-automatic framework, where the user manages and labels segmented blocks in an interactive manner. Connected components extracted by binarization are also used to build a direct mapping between shape/geometry and binary or color features [LBK04]. In a similar way, Baechler et al. [BBI10] rely on adaptive binarization to segment document layouts, and to provide the user with a semi-automatic annotation tool for the generation of ground truth of layouts for medieval manuscripts. However, binarization pre-processing produces uncontrollable errors, since it is sensitive to noise and to images with low dynamic range, as in the case of fading-out ink or stains. Further, most of them deal with very clean layouts, where the background, the text and the other entities are very easy to separate. For instance, advanced methods for text block identification and text line extraction are developed in extreme cases of very complex writing styles and languages, such as skewed and non-rigid deformed text [KC10], handwritten Arabic lines [SSG09], or chinese characters [KC12]. However, all of them act on datasets with a high contrast between background and foreground, so that the noise is not an issue and they limit the algorithm to cope with deformed shapes and complex nature of characters.

Conversely, some techniques do not need a binarization step [GSD11a]. This makes them more robust to noise, highly background variability, and ink bleed-through. Since they deal with gray-scale (or color) images, they usually employ local image features, and then train multiple classifiers from the corresponding 2D descriptors [GSD11b]. As recently pointed out by Pintus et al. [PYR13], although these methods can analyze the document layout without any priors about its physical and logical structure, their main drawback is that they all require some amount of user intervention. Since the semi-automatic nature limits the range of their applicability, and makes them unsuitable for massive and heterogeneous data analysis, they presents a multi-scale framework to automatically estimate the average per-page text leading value. This approach, applied as a pre-processing step, makes some of the previously mentioned state-of-the-art algorithms completely automatic.

Our work is inspired by this literature. Particularly, we use the text leading computation [PYR13] as a pre-processing step, in order to attain a completely automatic pipeline for text region segmentation and extraction of lines of text. Since we are dealing with very noisy and damaged dataset, we avoid the binarization pre-processing, as Garz et al. [GFSB12], and we employ robust local descriptors to classify text features [GSD11b]. The paper most similar to ours is Pintus et al. [PYR14], which presents a per-page text line extraction. Our contribution overcomes major limitations of this work. First of all, we employ a dedicated page voting framework to select the most representative pages from a book. This allows the training of a text classifier on a per-book basis. This is more robust than the previous per-page approach, which fails if the text leading is mis-computed (see [PYR13]) or in the cases of poor initial text segmentation (see [PYR14]). Further, to compute an automatic coarse text segmentation, we perform not only a multi-scale comparison, but we also use the amplitude of Fourier coefficients as a measure of the local text likelihood. Moreover, while the previous method is limited to pages with only one main text block, we exploit the sparse feature classification, together with a kdtree-based analysis of text points, to compute a more precise and dense text region segmentation. Thus, the proposed method provides a more general support for multiple text block identification, and allows us to find lines of text in a more reliable, versatile and efficient way. Finally, we show the robustness and reliability of our technique with an extensive evaluation performed on a large dataset with a high variability of layouts, syles, and levels of conservation.

3. Technique overview

Fig. 1 shows an overall view of the proposed layout analysis pipeline. The algorithm is given an entire book as a set of images. As a pre-processing step, for each page we compute the average text leading [PYR13], and the SIFT features [Low04]. By exploiting the information of the text leading distribution across the book and the hue histogram of each image, we select the most salient pages, and the corresponding local image descriptors. With a modification of the frequency based approach presented by Pintus et al. [PYR14] we compute a coarse two-class segmentation of this subset, and we assign to each feature one of the following labels: *text* or *non-text*. We use this rough classification to automatically train a Support Vector Machine (SVM) with Radial Basis Function (RBF), and we then re-launch a prediction step to all original SIFTs to obtain a fine text keypoints segmentation. Since the predicted points across the entire manuscript are a sparse representation of text positions, we employ a kdtree data structure to estimate the influence radius of each point, and we extract dense text regions and the associated rectangular text blocks. Finally, for each block we give the fine SIFT classification to an algorithm based on Projection Profiles (PP) [PYR14] in order to find lines of text. The highlighted parts (gray rectangles) represent the new elements proposed in this paper.

4. Method

The input data for our document layout analysis method is a complete image set of all pages from a manuscript. We don't have particular constraints on the nature of the data; the input may have ornamentation, portraits, figures, capital letters and touching and overlapping lines. The input may be degraded by background noise, fading-out and bleeded-through ink and other kinds of damage due to ageing. We make two minor assumptions, that are typically met in a general scenario. As in Pintus et al. [PYR13], the text should be quasi-horizontal, or a pre-processing step should be applied in order to correct the overall orientation of each page [PGLS13]; this is a common constraint in the capture and visualization systems of digital libraries and museums. Without loss of generality, we can assume that it is possible to model the behaviour of the per-page text leading value across a single book as a normal distribution, i.e. a pair of a mean and a variance value. The pipeline we present is completely automatic, and the parameters involved are set just once, and they are not data dependent or manually tuned by the user. Throughout this section, for display purpose only, we use pages from the book *BodleianMSBodley850* from the Yale University's Beinecke Rare Book and Manuscript Digital Library [Bei13b, Bei13a].

4.1. Pre-process

For each input image we extract local, sparse image keypoints and the corresponding descriptors; in this work we use SIFT features (Scale-Invariant Feature Transform) [Low04]. On the left of fig. 4) we show all the original SIFT features extracted for one page of the book. We also compute the average text leading value for each page of the manuscript [PYR13]. With the aim at a per-book basis approach, we consider the text leading as a discrete random variable, and we model its distribution across the manuscript as a Gaussian probability mass function. We find its *mean* μ and *variance* σ^2, and we use these as parameters to drive some of the following steps in our pipeline. From now on in the pipeline, for a page i we consider the associate text leading L_i as:

$$L_i = \begin{cases} L_i & \text{if } |L_i - \mu| < \sigma \\ \mu & \text{if } |L_i - \mu| \geq \sigma \end{cases} \quad (1)$$

4.2. Salient pages

To train a text descriptor classifier with a minimal subset of feature vectors, we want to automatically select the most representative pages from the input manuscript. These pages/images should contain both *text* and *non-text* keypoints, so that the training step can well separate the two classes in the feature space. For each page we compute two values: the text leading likelihood and the hue diversity. The

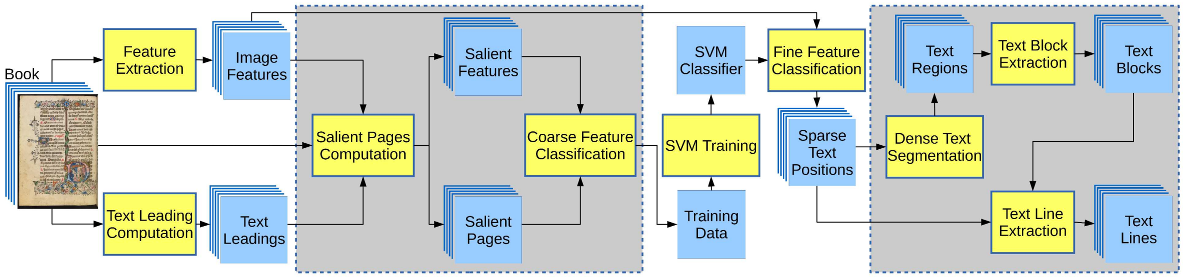
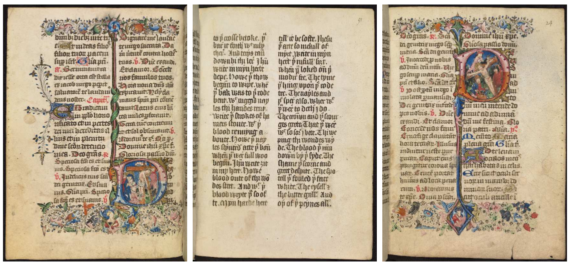


Figure 1: ***A TaLISMAN - Algorithm pipeline.*** *Given a book, we extract per-page text leadings and features. We select the most salient pages and image descriptors, and we compute a rough text segmentation that we use to train a SVM classifier. We re-launch the prediction to all original features to obtain a fine segmentation. We convert these sparse text positions into a dense text region representation, and we finally extract text blocks and lines.*



(a) (b) (c)

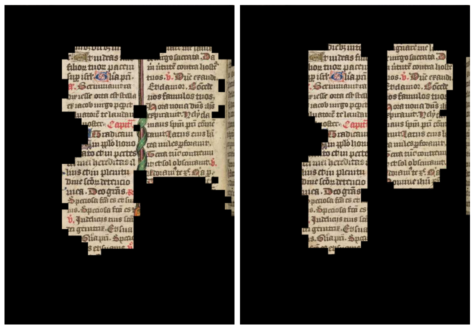
Figure 2: ***Salient images.*** *They contain a good sampling of both* text *and* non-text *keypoints, to well separate the two classes in the feature space.*

text leading likelihood p_i for the page i is defined as:

$$p_i(L_i) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{1}{2}\frac{L_i - \mu}{\sigma^2}} \quad (2)$$

After converting the image into a *HSV* color space, the hue diversity h_i is the number of non-zero bins in the hue histogram of the selected page. The number of bins in the hue histogram is fixed to 180, and we use this value in all our tests. Now we extract $3N_S$ salient pages following three steps. We first sort the pages by decreasing hue diversity, and we take the first N_S images; these are pages with a lot of figures, capital letters and drawings. We then sort the pages by decreasing text leading likelihood, and we consider just the subset of pages with likelihood bigger than 0.5; according to Pintus et al. [PYR13], these are pages that more likely contain well formatted and regularly distributed text. We sort this subset by increasing hue diversity, and we take the first and the last N_S images; these are respectively the images containing regular text but a limited amount of drawings, and images with both regular text and a lot of figures. In all our experiments we found $3N_S = 6$ a reasonable value; the bigger this value, the bigger the training dataset, and the more time consuming will be the training of the classifier.

Fig. 2 shows three of the six extracted salient pages, one for each type: fig. 2(a) is the page with the highest hue diversity value, fig. 2(b) contains only text and it is the page with the highest text likelihood, while the last (fig. 2(c)) is the page that, among the pages with high text likelihood, has the biggest hue diversity value. The output of this step is a list of images, and the corresponding local feature descriptors and text leading values.



(a) (b)

Figure 3: ***Coarse text segmentation.*** *Comparison between our method (b) and the method of Pintus et al. [PYR14] (a). We superimpose coarse text masks and original images to show how the proposed use of coefficient amplitudes strongly improve the segmentation of* text *(bright) and* non-text *(dark) pixels.*

4.3. Coarse text segmentation

We perform a coarse segmentation of the feature vectors from the salient images, to assign to each of them a label (i.e., *text* or *non-text*). First we compute a coarse, binary (black/white) mask to identify the text pixels in each image. We modify the approach of Pintus et al. [PYR14]. For each salient page, the knowledge of the text leading L_i, and a frequency-based analysis [PYR13], allow us to build an operator to coarsely estimate the probability that a pixel belongs to a text region. Given a pixel, a window of size nL_i centered at that pixel is considered, and we compute the y-axis projection profile of its normalized autocorrelation function [PYR13]. From a frequency analysis of the profile, if the pixel happens to be in a text region, the maximum coefficient index i of the Discrete Fourier Transform (DFT) will likely be equal to n. Rather than a binary *Yes/No* decision [PYR14], if this condition is met, the probability of the pixel to be within a text part is evaluated as the maximum DFT coefficient amplitude normalized by the window size. To increase the robustness we do the same computation with more window sizes, and we average the resulting probabilities; as in [PYR14], we choose a range for n equal to $[2,N]$, with $N = 5$. This is a good choice in terms of reliability and computational time, and we fix this value for all the tests in section 5. At the end of the process we have a probability field in the image domain that we binarize by using a straightforward k-means clustering. We compare our coarse segmentation (fig. 3(b)) and the method of Pintus et al. [PYR14] (fig. 3(a)); the bright regions are *text* pixels, while dark ones are *non-text*. As expected, the proposed use of coefficient amplitudes strongly improves the segmentation result. Then, we take all the SIFT keypoints for a particular salient image, and we label them by taking into account both the text leading and the coarse mask. For each keypoint we consider its position in the image and its scale. *Non-text* keypoints lie outside the *text* region of the mask, and have a scale that is not compatible with the page text leading. Otherwise, we set it as a *text* keypoint. The keypoints that most of all represent text characters have a size between the 5% and the 25% of the text leading [PYR14]. We choose this fixed range in all our experiments. Keypoints after this pruning are depicted in fig. 4(b). The output is a set of descriptors from all salient images, each with a label: *text* or *non-text*.

4.4. Fine text segmentation

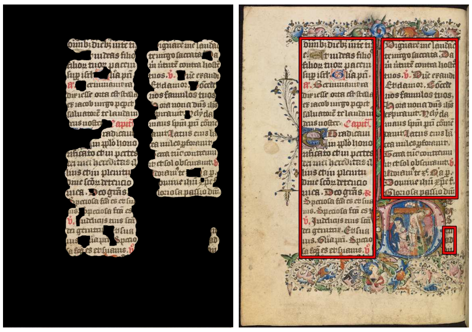
The set of roughly segmented descriptors is used as an initial classification to train a robust Support Vector Machine model (SVM) with a Gaussian radial basis function as kernel. We found that this type of statistical model is well suited for our problem, as in other works [GFSB12, GBC11]. Once the SVM is trained, we consider it as a per-book text classifier. We then launch a prediction step over all the original SIFT descriptors from the entire book. This gives us a refined text feature classification across all our pages. Fig. 4(c) shows the text keypoints after the prediction step applied to all the features in fig. 4(a). In the last column (fig. 4(d)) we compare the coarse and fine segmentations for a small region. The former roughly identifies the overall text regions. However, the refinement step both recognizes more precisely the text characters, as in the borders of text columns, and gets rid of the descriptors in the figures, as in the case of one-line capital letters across the main text body, which are more similar to drawings than common characters. The output is a list of text keypoint positions for all the pages in the book.

4.5. Text regions

Text keypoints are a sparse set of text character positions in the image domain. We want to obtain a dense representation of text regions, so that we can use this information to find other layout entities such as main text blocks and lines. We start by populating a two-dimensional kdtree structure with the sparse points extracted in the previous step. For each of these points we perform a nearest neighbors search in order to estimate its radius of influence in the 2D domain. First we order the neighbors by their distance to the selected point. We then compute their centroid, and the radius of influence will be the distance between the centroid and the median neighbor. We define a maximum allowed radius for the page i as:

$$R_{max}(i) = \begin{cases} 2(L_i + \sigma) & \text{if } |L_i - \mu| < \sigma \\ 2(\mu + \sigma) & \text{if } |L_i - \mu| \geq \sigma \end{cases} \quad (3)$$

We remove points as outliers if they have radius bigger than $R_{max}(i)$, and distance from the centroid is bigger than their radius. In this way we prune likely wrong or isolated points. Finally, we get a dense text mask by looping on all image pixels, and by assigning a *text* label to all of them that lie within at least one of the computed areas of influence. We refine the dense mask by performing a *dilate* and *erode* operation to remove holes and small isolated regions. The dilation and erosion kernel is driven by the value of the per-page text leading; particularly, we fix the size of the morphological kernel as a quarter of the text leading. In fig. 5(a) bright areas depict the segmented dense text regions. The output is a binary mask for each manuscript page, where 1 means text region, and 0 the remaining part of the page.



(a) (b)

Figure 5: ***Dense text regions and main text blocks.*** *We convert the sparse set of text features into a dense text region segmentation. In (a) we superimpose the dense text mask and the original image. We use connected components in the dense text mask to retrieve main rectangular text blocks (b).*

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

Figure 4: ***Text feature coarse segmentation.*** *We present the various steps of the proposed text keypoint classification: a) Original SIFT keypoints; b) keypoints after the pruning based on the coarse text mask and the estimated text leading; c) keypoints marked as* text *after the fine segmentation performed with the trained, per-book SVM classifier. The last column (d) depicts the three steps for a detailed view of the page.*

4.6. Text blocks and lines

It is possible to exploit the layout information from the previous steps to obtain a more detailed analysis of the document structure. We demonstrate how the presented completely automatic per-book framework for dense text segmentation could be used to extract main text blocks and text lines.

Retrieving text blocks is straightforward; they are the minimum size rectangular regions that include the connected components of the dense text mask. Given the mask in fig. 5(a), we find three connected components (bright areas), and thus the three text blocks in fig. 5(b).

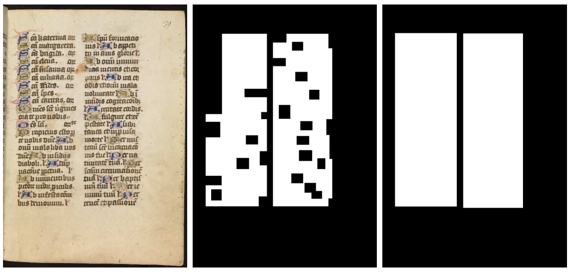
To segment lines of text, we apply the approach introduced by Pintus et al. [PYR14], which is a modification of the original Projection Profile algorithm [LSZT07]. For each text block we take the *text* keypoints, and we integrate only their contribution over the rows. Rather than performing a one-pixel resolution integration, we set the bin size of the resulting profile proportional to the known per-page text leading. Small bin sizes (e.g., one pixel) will result in a noisy signal; conversely, large bin sizes will have a poor resolution, and the information about text lines will be lost. We fix bin size as a quarter of the per-page text leading, and use this value for all our tests in Section 5. We then find all the maxima in the profile by using as tolerance the text leading value. Since for some applications, such as text transcription and annotation, or word spotting, an image of the single text line is required, the output is a list of sub-images. For each line, we export a sub-image centered at the retrieved text line (i.e., (x,y) centroid coordinate of the row corresponding to the profile maxima), with the width equal to the text block width. The height will be defined by the two minima of the profiles, one above and one below the y coordinate of the line, and within a search interval of $\pm L_i$. Depicting all text lines in a single image could be confusing, so fig. 6(a) and fig. 6(b) show respectively the retrieved odd and even lines.

(a) (b)

Figure 6: ***Text lines.*** *We show the automatically retrieved odd (a) and even (b) lines of text.*

5. Results

We apply the proposed method to 8 medieval handwritten books, with 2724 pages, 3558 text blocks and 65697 lines. They are from the list of books provided in the database of the Yale Digital Collection Center [Bei13b, Bei13a]. The data are very heterogeneous, in terms of layout structure (e.g., number of columns and text density), conservation (e.g., ageing, ink bleed-through and noise), resolution, and writing styles. The algorithm was implemented and tested on a Linux platform, using C++ and the OpenCV library [Ope13]. The benchmark were launched on a Desktop PC with 8 Intel Core i7-3820 CPU @ 3.60 GHz processors, and 64GB RAM. We performed two different kinds of evaluations, in order to understand the level of quality and reliability of the proposed technique.



(a) (b) (c)

Figure 7: ***Manual segmentation.*** *We show an example of manual segmentation performed on the original image (a). We created a mask for the text region (b), and rectangular boxes for the main text blocks (c). Similarly we produced* 44 *masks for the text lines with a single rectangular box each.*

In the first type of evaluation, we randomly took a set of 56 images/pages from all the books, with 66 text blocks and 1295 lines. We manually segmented text regions, blocks and lines. For each text region and block we created a single binary mask. Conversely, we produced a mask for each line of text. In the case of lines or blocks, we used the constraint that the segmented part must be an up-right rectangle. Fig. 7 shows an example of manually produced masks for a page in the ground truth dataset. We did not mark as *text* one-line capital letters (fig. 7(b)), since in our framework we consider them as drawings, figures or ornaments (see also fig. 4(d)). For the sake of simplicity, we omit to show the 44 masks corresponding to the text lines, but they are created similarly as the text block mask.

Then, we compare the ground truth (manually defined) masks with those automatically computed by our algorithm. For each pixel position k in the page we see if it is a *true-positive* (TP), a *false-positive* (FP), or a *false-negative* (FN). We analyze the pair $\left(p_m^k, p_a^k\right)$, where p_m^k and p_a^k respectively are the values of the manually and the automatically computed mask: a *true-positive* $(1,1)$ is a corrected segmented pixel; a *false-positive* $(0,1)$ is a pixel that is recognized as *text* but it is not (also known as *false alarm*); a *false-negative* $(1,0)$ is a pixel that is marked wrong as *non-text* (also known as *miss*). Table 1 shows the resulting numerical statistics, and we report the corresponding *Precision* and *Recall* values as:

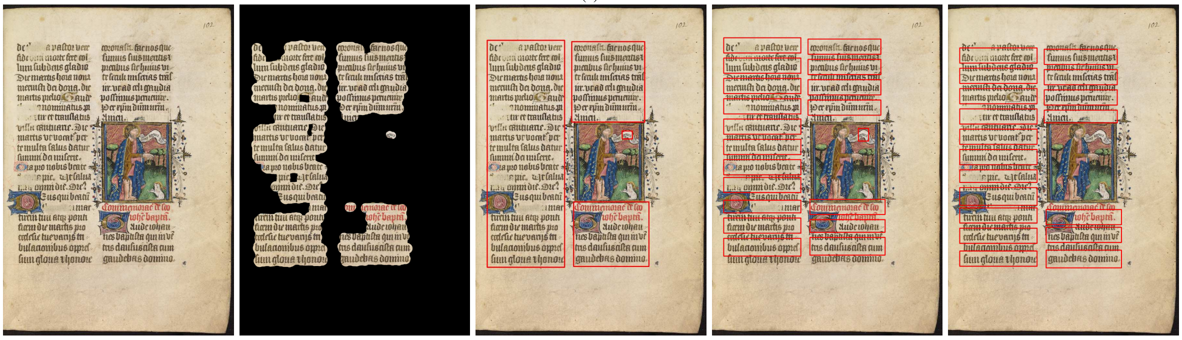
$$\begin{cases} Precision = \frac{TP}{TP+FP} \\ Recall = \frac{TP}{TP+FN} \end{cases} \quad (4)$$

The *Precision* means the probability that a randomly selected pixel is relevant (TP), while the *Recall* is the probability that a randomly selected *text* atom (i.e., a pixel belonging to a text region, block or line) in the database will be retrieved in a search. As we can see, all the values related to regions and blocks are above 90%. For text lines we have a very good *Recall* value (about 98%), but, since we apply a conservative sub-image text line extraction (e.g., for applications as manuscript transcription or word-spotting), we lack a high *Precision* value (about 70%).

The evaluation just described is only practical for a small subset of images, while we would like to check all the thousands images in our database. We employ a visual computer assisted check. Since it is very difficult to visually estimate the quality of the text region segmentation, we perform this evaluation for text blocks and text lines only. In the first case, for each page, the algorithm draws all the blocks within the image; on the other hand, for each line it outputs an image with a highlighted rectangular region that includes the single extracted line. Both for blocks or lines, we visually inspect them and manually mark them as TP, FP or FN; then we compute the resulting *Precision* and *Recall* as in eq. 4. Although this is a *ON/OFF* judgement, we can produce statistics for a large number of pages (see Table 2 and 3). Compared to the work of Pintus et al. [PYR14], our per-book approach significantly increases the *Recall* value in the text line segmentation. On the other hand, the *Precision* is less. In fact, their per-page approach completely fails in pages with non-regular text (fig. 9(d)), so it has a lot of missing text lines (low *Recall*), but small number of *false positives* (high *Precision*). Instead, our approach is able to analyze those images, but, while it decreases the number of missing records, it produces some *false alarms* (fig. 9(d)). However, we can see how the fluctuation of the *Precision* value is an acceptable outcome, compared with the obtained *Recall* value, which is generally very closed to 100%. In some applications (e.g., transcription or word spotting), it is better to have *false alarms* than missing text lines. The similar results for text block segmentation show the reliability of the proposed technique. In Table 2 we cannot compare the results for *MarstonMS22*. It is a one column book with two pages per image; since the lines from different pages are perfectly aligned, Pintus et al. [PYR14] consider this to have a single main text block per image, and extract two lines at a time. In our work here we classify this as a two column book.

Pages in old books contain text in one or more colors, capital letters with drawings, the parchment, other figures or ornaments. Moreover, each image could contain acquisition background, other visible parts of the book, and, in some cases, rulers or other measurement tools. Fig. 8(a) and 8(b) are a typical complex but clear cases, where the pages are well preserved and do not contain imperfections. On the other hand, most of the problems arise when dealing with more challenging pages. To appreciate the quality of our new approach, we show here results related to pages affected by significant ageing (fig. 9), and very bad preservation conditions (fig. 9(b)), or with the presence of additional marginalia (fig. 9(e)). Fig. 9(c) shows an extreme case, where the page contains noise, few lines of text, a lot of added signs, and ink bleed-through.

(a)



(b)

Figure 8: ***Illuminated manuscript pages.*** *We present here the segmentation results of typical pages from illuminated medieval books with one (a) and two (b) column layout.*

Table 1: ***Quantitative evaluation.*** *Classification error compared to a manual segmentation.*

	#items	True-positive	False-positive	False-negative	Precision	Recall
Text regions	NA	∼196Mp	∼14Mp	∼18Mp	93.54%	91.60%
Text blocks	66	∼245Mp	∼11Mp	∼3Mp	95.88%	98.97%
Text lines	1295	∼262Mp	∼117Mp	∼5Mp	69.06%	98.22%

6. Conclusion

We have presented a method to perform automatic layout analysis of very old handwritten manuscripts. It retrieves text regions, text blocks and text lines, with no manual intervention and user defined parameters. We have tested our algorithm on a large and heterogeneous corpus content, and assessed its reliability both in a quantitative and qualitative manner. Future work will focus on investigating other possible local image descriptors that might be more suitable for handwritten text, and more efficient and scalable machine learning algorithms to manage large scale training datasets.

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Table 2: ***Text line segmentation statistics.*** *Visual qualitative check.*

Book Name	Lines	True-positive [PYR14] / Our	False-positive [PYR14] / Our	False-negative [PYR14] / Our	Precision [PYR14] / Our	Recall [PYR14] / Our
One column books						
Osborna44	9277	8384 / 9187	3 / 277	893 / 90	99.96% / 97.07%	90.37% / 99.03%
BeineckeMS109	4616	4511 / 4570	62 / 118	105 / 46	98.64% / 97.48%	97.73% / 99.00%
BeineckeMS310	5299	4967 / 5246	62 / 262	332 / 53	98.77% / 95.24%	93.73% / 99.00%
BodleianMS2.11	7576	7038 / 7333	273 / 122	538 / 243	96.27% / 98.36%	92.90% / 96.79%
BeineckeMS360	8186	8041 / 8038	113 / 690	145 / 148	98.61% / 92.09%	98.23% / 98.19%
Two column books						
MarstonMS22	2983	NA / 2966	NA / 59	NA / 17	NA / 98.05%	NA / 99.43%
BodleianMS850	9620	NA / 9015	NA / 444	NA / 605	NA / 95.31%	NA / 93.71%
SanktGallen673	18140	NA / 17314	NA / 334	NA / 826	NA / 98.11%	NA / 95.45%
# books - 8	65697	NA / 63669	NA / 2306	NA / 2028	Na / 96.50%	NA / 96.91%

Table 3: ***Text blocks segmentation statistics.*** *Visual qualitative check.*

Book Name	Blocks	True-positive	False-positive	False-negative	Precision	Recall
BeineckeMS109	256	253	25	3	91.01%	98.83%
BeineckeMS310	463	417	24	46	94.56%	90.06%
BodleianMS2.11	548	542	44	6	92.49%	98.91%
MarstonMS22	233	232	23	1	90.98%	99.57%
BeineckeMS360	389	378	184	11	67.26%	97.17%
Osborna44	568	541	155	27	77.73%	95.25%
BodleianMS850	512	476	185	36	72.01%	92.97%
SanktGallen673	589	568	219	21	72.17%	96.43%
# books -	3558	3407	859	151	79.86%	95.75%

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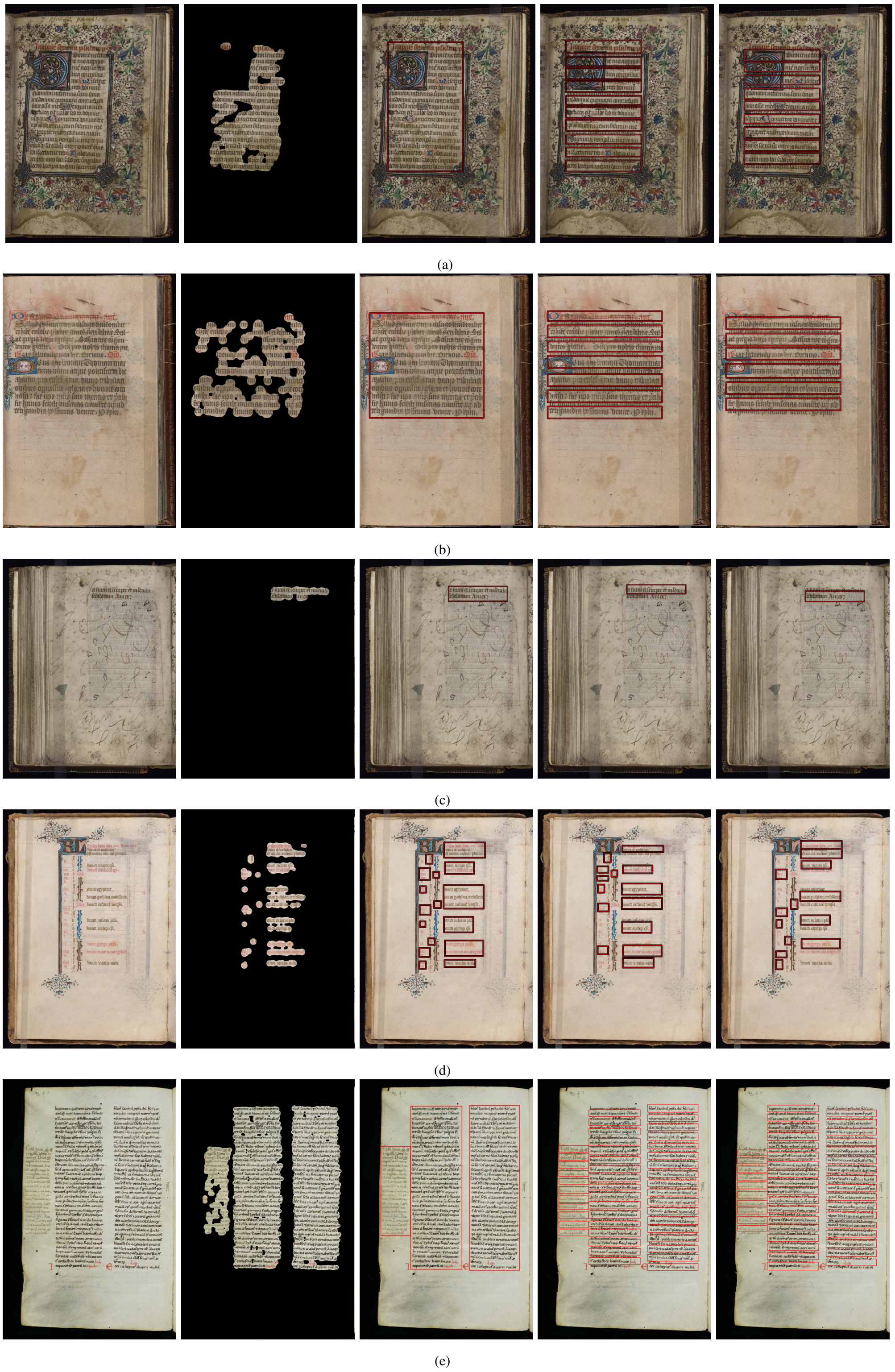

Figure 9: ***Challenging pages.*** *We present here the segmentation results of pages in the case of: (a) ageing; (b) damages; (c) noise, ink bleed-through and with small number of text lines; (d) non-regular text; (e) marginalia.*