# On Learning-free Detection and Representation of Textline Texture in Digitized Documents

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Abstract: Textline detection and extraction is an integral part of any document analysis and recognition (DAR) system bridging the signal2symbol gap in order to relate a raw digital document of whatever sort to the computational analysis up to understanding of its semantic content. Key is the computational recovery of a rich representation of the salient visual structure which we conceive texture composed of periodic and differently scaled textlines in blocks with varying local spatial frequency and orientation. Our novel learning-free approach capitalizes on i) a texture model based upon linear system theory and ii) the complex Gabor transform utilizing both real even and imaginary odd kernels for the purpose of imposing a quadrilinear representation of textline characteristics as in typography. The resulting representation of textlines, be they either linear, curvilinear or even circular, then serves as input to subsequent computational processes. Via an experimental methodology allowing for controlled experiments with a broad range of digital data of increasing complexity (e.g. from synthetic 1D data to historical newspapers up to medieval manuscripts), we demonstrate the validity of our approach, discuss success and failure, and propose ensuing research.



## 1 INTRODUCTION

Textline detection – and extraction as a related problem e.g. in the context of layout analysis – is a well-researched DAR topic since decades. The known methods span the range from bottom-up learning-free to machine learning methods and the latemost ICDAR competition (Diem et al., 2019) convincingly elucidates the attained performance level. However, as yet the DAR focus was mainly set on baseline detection, whereas our novel approach goes well beyond since we detect four lines related to the typographical line system for quadrilinear scripts: base- and top-lines as well as mid-lines of both the textline itself and the space between textlines. Such lines with a unique semantics are important for the measurement of saliency of quadrilinear scripts: Whereas the mid-line of the textline itself is self-explanatory, the base- and top-lines are delimiters of minuscule scripts while the mid-line of the interspace along with the neighbouring base- and topline index the potential margin space for appearance of descenders, ascenders, majuscules and/or even diacritics. Note that the distance between descender and ascender margins in two consecutive textlines is coined lead(ing) or slug though no standard definition exists. Moreover the distance between mid-lines of textlines in a regular textblock is related to the local spatial frequency while the distance between base-lines renders possible the typographical classification of normal, compress, and splendid. Hence the four lines, to be understood as a local semantically rich representation system, serve as local search space for visually salient textline features or, in other words, as a local signage system for subsequent computational processes in a task-oriented DAR system (see (Diem et al., 2013) for an epitome of a potential real-world use case drawing on word-signaling profile boxes).

As already mentioned, differently scaled textlines with blockwise varying local spatial frequency and orientation are conceived visual texture relating textline detection to texture detection. Visual texture is a multi-facetted phenomenon tackled by findings from visual neurosciences, visual psychophysics of e.g. arbitrary gratings, cognitive reading science, Gabor transform from linear system theory, photogrammetry-based remote sensing and scene analysis – you name it. Non-surprisingly past DAR research exploited the treasure trove of bottom-up approaches and – given the plethora (see (Binmakhashen and Mahmoud, 2019) for a recent survey) – in particular the well-understood Gabor transform



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made it into the DAR toolbox (see Chpt. 2 for some seminal work). However, to the best of our knowledge, past work drew upon the energy and/or the kernel orientation of the Gabor transform only thus ignoring the potential of the complex (real even and imaginary odd) notation. While energy (with its orientation) alone was proven to be successful in textline detection and even layout analysis, it lacks the capability of computational measurement of the above mentioned system of lines. Even more, the tacit assumption was textline regularity in terms of both spatial frequency within a horizontally aligned text block (e.g. main text in an Arab manuscript) and orientation (e.g. in the case of rotated commentaries). Regularity evidently is the ideal case (e.g. historical newspapers) while irregularities are prevalent due to varying cultural epoch, script, writing school, hand, production etc. thus posing challenges to DAR systems for OCR up to hand identification. Typically regularity is bound to height, contrast, distance, and orientation of textlines in digital documents. In contrast, irregularity is any deviation but also implies deviation from the ideal linear case of textlines which may be bended due to e.g. a hand's purpose or by accident during digitization (let alone the range of document degradations). As a consequence past research also focused on computational methods being tolerant to local irregularities (see seam carving as prominent example (Arvanitopoulos and Süsstrunk, 2014)) but as yet no all-in-one solution exists due to the variety of irregularities in the document domain.

With the revival of machine (and particularly the advent of deep) learning came along a paradigm shift from bottom-up computational vision e.g. for visual feature detection – disparaged as hand-crafted while ignoring the formal grounding – and representation to, say, empiricism-driven learning algorithms. Whilst achievements and breakthroughs – particularly in object classification for still images as for certain DAR tasks – have to be acknowledged, the sobering limits also came to surface, to name a few challenges (see e.g. (Yuille and Liu, 2021), (Drummond, 2006) and (Guidotti et al., 2018)): capability of adaption to a grand variety of data and tasks in DAR, sparseness and imbalance of training data, lack of ground truth, experimental methodology beyond current scalar-based metrics, dependency on tramontane platform providers as well as the black-box issue – let alone the evenly critical issue of complexity mastering by developers or non-tech-savvy users with demand for workflow support in their daily, e.g. scholarly or routine, work with DAR systems. As one consequence, current research on interactive machine learning aims at bringing the user with her/his intelligence back in the loop and in control. Our learning-free approach to textline detection and representation thus is guided by the heretical question "Why should we first learn what we already know?" – simply since in our case it is well known that in the first layers of some deep nets primarily "Gaborish" filter kernels are arduously learned ((Zeiler and Fergus, 2014), (Springenberg et al., 2015), (Krizhevsky et al., 2017)), but devoid of theoretical grounding as common in low-level computer vision. In the chapters to follow we outline the theory behind our learning-free approach, illustrate the validity via our 1D model of textlines as texture, describe our OpenCV-based 2D implementation and present experimental results[1] as a conclusive proof-of-concept for the cases of linear and curvilinear textlines in retro-digitized documents as well as of even circular epigraphic textlines in digital images of ancient bowls. Eventually we attempt to surmount the dichotomy of neat math and DARing needs of users as posed by Lopresti and Nagy one decade ago in their influential paper "When is a Problem Solved?" (Lopresti and Nagy, 2011).

## 2 RELATED WORK

As mentioned above, much work has been done on textline extraction and particularly baseline detection (see (Diem et al., 2019) for state-of-the art results of the 2019 cBAD competition) as such but – apart from lack of space – due to our focus on the texture-side of textlines in digital documents we here only review matching papers. The fact that the Gabor transformation plays a key role in computational texture analysis per se (see (Humeau-Heurtier, 2019) for a recent comprehensive survey) was early recognized in the DAR community (see recent reviews by (Mehri et al., 2017) and (Eskenazi et al., 2017)).

As a two-fold summary, first, despite the popularity of the Gabor transform in the DAR domain so far only local and/or directional filter energy measures have been used for, e.g. more recently, texture-based textline segmentation (Chen et al., 2014) and texture-exploiting binarization (Sehad et al., 2019). Second, the bulk of line detection approaches was tailored to baselines and, again to the best of our knowledge, in DAR no machine learning approach (see surveys in

[1]Please note that due to our University's pandemic-driven lab access restrictions since more than one year the planned number of joint experiments in our lab had to be trimmed. Further results of our web-based experimentation beyond the reported proof-of-concept are made available via https://www.inf.uni-hamburg.de/en/inst/ab/bv/publications.html

(Liwicki and Liwicki, 2020), (Lombardi and Marinai, 2020) and (Subramani et al., 2020)) to visual texture detection in digital documents aiming at computational measurement of textline features in a quadrilinear reference system is available as yet.

Interestingly, already in 2007 Likforman-Sulem et al. (Likforman-Sulem et al., 2007) in their early survey stressed the importance of visual characteristics as well as representation of text lines, e.g. baseline, median line, upper line, and lower line in their notation, for textline segmentation. In their vein, recent research has been reported on learning-free beyond-baseline detection drawing upon computational vision milestones. Manmatha and Srimal (Manmatha and Srimal, 1999) at first applied the then well-established scale space theory to segmentation of hand-written words via i) scaled anisotropic Laplacian-of-Gaussian operators and ii) scale selection for blob detection resulting in bounding boxes for words. Later on, Cohen et al. (Cohen et al., 2014) also used the anisotropic directional Gaussian kernel $G(\sigma)$ along with its $2^{nd}$ order derivatives at multiple scales for textline extraction by scaling $G(\sigma)$ to the average textline height. On this basis, Saabni et al. (Saabni et al., 2014) proposed an approach to impose so-called seams on binary/gray-scale images (inter alia using an energy map derived from a signed distance transform) passing across/between textlines thus approximating their upper/lower boundaries.

In a recent follow-up paper on language-independent - though computationally expensive - text line extraction for handwritten gray-scale documents with near-horizontal or fluctuating lines, Azran et al. (Azran et al., 2021) proposed a combination of two known CNNs resulting in an energy map. In a second step, minimal energy sub-seams are tracked and accumulated "...to perform a full local minimal/maximal separating and medial seam defining the text baselines and the text line regions." (trilinear representation).

In like manner to (Cohen et al., 2014), Aldavert and Rusinol (Aldavert and Rusiñol, 2018) attempted streak-like representations of textlines (varying in height, orientation and bending) utilizing scaled oriented $2^{nd}$ order Gaussian derivatives again with $\sigma$ proportional to line height.

Current work by Barakat et al. (2020) (Barakat et al., 2020) described a method based upon $2^{nd}$ order derivatives of anisotropic Gaussian filters (with automatic scale selection), energy minimization and graph cuts for detecting so-called blob lines that strike through text lines with an admissible skew and bending (see also their companion paper linking their previous work to CNN (Barakat et al., 2021)).

Lately, Mechi et al. (Mechi et al., 2021) proposed a complex two-step framework for text line segmentation (for Arabic and Latin manuscripts) which comprises both a deep FCN model and a post-processing based on topological structural analysis. Through copious FCN benchmarking, they experimentally demonstrated superiority of the adaptive U-Net model which yields a two-line (namely base- and top-line, or synonymously, X-height) representation enhanced by a rather sophisticated post-processing step for extraction of complete text lines (including both the ascender and descender components). Experimental results of the two-step architecture revealed a 97/99% correctness of text lines given ANT-A/ANT-L datasets [2].

Taken together, so far learning-free line detection as well as representation in the first place capitalized on scaled anisotropic – ergo oriented – $2^{nd}$ order Gaussian derivatives matching textline height whereas - as will be elucidated below - the complex Gabor transform renders possible both bottom-up detection of line-line texture and its quadri-linear representation borrowed from typography/paleography.

# 3 OUR APPROACH

As sketched above, we ground our approach on linear (LTI) system theory in order to i) model the structure of visual texture at hand and ii) derive convolution kernels via the complex Gabor transform. For reason of convenience we briefly introduce the 1D case only since generalization to 2D is straightforward (see also below).

Let $I(x,y)$ be a digital document (or, tout court, image $I$ with $x$/$y$ for columns/rows and its origin in the upper left corner) and $I(x = const, y) \equiv I(y)$ a vertical section. Then an idealized, viz binary, 1D model of both a black-inked textline and a white interspace is a rectangular pulse $P(y)$ with either negative or positive polarity. Since for the latter case $P(y)$ can be composed from two shifted Heaviside functions $H(.)$, $P(y) = H(y) - H(y-w)$ holds with $w$ as pulse width (see fig 1). Note that for modeling of varying contrast, constants can easily be included. Since a pulse of whatever polarity has two Heaviside flanks of inverse polarity and a mid-point at its center, four salient visual features are defined: Points of ascending/descending flanks of a pulse and mid-points of a positive/negative pulse – which in 2D generalize to the above mentioned four lines: base-/top-lines and textline/interspace midlines.

[2] http://www.archives.nat.tn/

Since the mentioned flanks of a pulse are of odd nature with inverse polarity whereas the pulse (be it of positive or negative polarity) is even, the complex Gabor transform comes into play with both even and odd kernel

$$\begin{aligned}\mathscr{G}(y) &= G(y;\sigma)\cdot\exp\left(j\cdot\frac{2\pi y}{\lambda}\right)\\ &= G(y;\sigma)\cdot\left[\cos\left(\frac{2\pi y}{\lambda}\right)+j\cdot\sin\left(\frac{2\pi y}{\lambda}\right)\right]\end{aligned} \tag{1}$$

with the Gaussian envelope $G(y;\sigma)=\frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{y^2}{2\sigma}}$ and $\lambda$ as the wavelength of the sinusoidals. The Gabor transform as convolution then reads as $\mathscr{T}(\mathscr{G}(y)) = I(y)\otimes\mathscr{G}(y)$ with its result coined response map $\mathscr{R}(y)$.

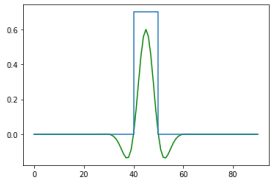
Note that the convolution kernels map to filters in the frequency domain with tunable mid frequency and bandwidth rendering possible a best match with local spatial frequency content.

Evidently both the real even and the imaginary odd parts are required as convolution kernels (in the sense of matched filters) in order to detect the above mentioned four salient features. Moreover, as a more than welcome side effect, each kernel with a specificity for just one of the four salient points bears an implicit semantics yielding four pre-classified response maps (or feature channels). For the detection of the extrema in the response maps, the criterion $\frac{\mathrm{d}}{\mathrm{d}y}\mathscr{R}(y)\stackrel{!}{=}0$ must hold. In fig. 1c and 1d the local extrema are indicated by the vertical lines, which represent the mid- and top-line of the interline space.

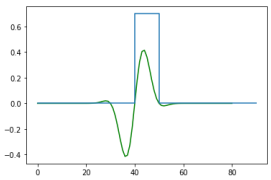
Since the implicit convolution of both the Heaviside functions and the rectangular pulse (being distributions not functions in the common sense) with a Gaussian kernel implies their regularization, resulting extrema at the mentioned points can easily be detected. However, as pointed out below, in the case of the rectangular pulse the kernel width of the even Gabor kernel has to match the pulse width for an unique extrema giving rise to the necessity of appropriately selecting the scale $\sigma$ of the Gaussian.

Line texture now can trivially be modeled in 1D by a linear combination of rectangular pulses with degrees of freedom allowing for varying local frequency via a change of the width of neighboring pulses of opposite polarity (forming an antisymmetric pair modeling textline and interspace in 1D). Clearly the ideal case in terms of texture regularity is a linear combination of antisymmetric pairs of pulses for which the four salient line features can easily be detected via the above mentioned two kernels of the complex Gabor transform. In the case of texture irregularity, however, a careful analysis of the Fourier phase space is required.

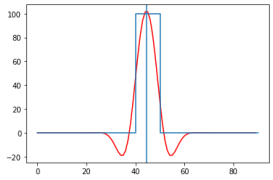
For the case of 1D regularity in $I(y)$, the following fig. 1a and 1b illustrate the core of our approach.



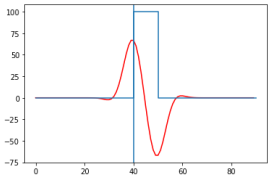
(a) Positive pulse with width-matching even Gabor kernel.



(b) Positive pulse with flank-matching odd Gabor kernel.



(c) Response map for (a) with extremum at mid-point of pulse.



(d) Response map for (b) with extrema at flank of pulse.

Figure 1: Principle of detecting salient points at positive pulse (aka interline space model).

As known the 1D Gabor kernel generalize to 2D without ado (Henriksen, 2007) for both the real even and imaginary odd part:

$$\mathscr{G}_{Real}(\mathbf{p}) = \exp\left(-\left(\frac{x'^2}{\sigma^2}+\frac{y'^2}{(\frac{\sigma}{\gamma})^2}\right)\right)\cos\left(2\pi\frac{x'}{\lambda}\right) \tag{2}$$

$$\mathscr{G}_{Img}(\mathbf{p}) = \exp\left(-\left(\frac{x'^2}{\sigma^2}+\frac{y'^2}{(\frac{\sigma}{\gamma})^2}\right)\right)\sin\left(2\pi\frac{x'}{\lambda}\right) \tag{3}$$

where

$$\begin{aligned}\mathbf{p} &:= (x,y;\lambda,\theta,\sigma,\gamma)\\ x' &= x\cos\theta + y\sin\theta\\ y' &= -x\sin\theta + y\cos\theta\end{aligned}$$

and $\lambda$ as the wavelength of the wavefronts, $\theta$ as the orientation of the kernel, $\sigma$ as the standard deviation along x' and $\gamma$ steering the anisotropy of the Gaussian along y'. However it is worth recalling that in 2D two more degrees of freedom have to be considered, viz the orientation of line-like texture and the anisotropy of the Gaussian determined by its covariance matrix or, respectively, the aspect ratio (implying a tradeoff between frequency and orientation sensitivity). Having said that, the 2D complex Gabor transform reads as $\mathscr{T}(\mathscr{G}(x,y)) = I(x,y)\otimes\mathscr{G}_X$, where $\mathscr{G}_X\in\{\mathscr{G}_{Real},\mathscr{G}_{Img}\}$.

In other words, a fully-fledged 2D Gabor transform spans a solution space $S(\lambda,\theta,\sigma,\gamma)$ for 2D visual texture with dimensions anisotropy/orientation

of Gaussian and frequency/orientation of sinusoidal wave fronts. As a consequence, $S(\lambda, \theta, \sigma, \gamma)$ has to be explored for extrema in order to detect spatially varying local texture with high precision which relates to both Gaussian scale-space and wavelet theory. However, as laid out with acuity in (Lee, 1996), although the 2D Gabor transform with the Gabor kernels from Equ. 2 and 3 achieves the resolution limit, it does not fully satisfy wavelet theory due to an existing d.c. component of the even kernel (see (Lee, 1996) sec. 2 for details and a derivation of – still nonorthogonal – Gabor wavelets).

In our case, since the Gabor transform utilized is the standard complex one (with kernels provided by OpenCV for the sake of convenience; see also below), a solution to our visual texture detection problem in digital documents requires some further thoughts. First, in terms of regularity, we assume digital document images (or, synonymously, pages from e.g. manuscripts, codices or newspaper collections) to obey block-wise texture regularity due to constancy in writing school, hand or print typeface barring admissible deviation. Thus, secondly, as yet we only allow for spatially regular composition of textlines varying in height, interline spacing, orientation but also curvature of rather arbitrary radius. In order to constrain the mentioned full solution space S(.), in the following a pragmatic approach will be presented which i) capitalizes on prior domain/task knowledge embedded in an interactive scenario and ii) serves as proof-of-concept.

## 4 EXPERIMENTS AND RESULTS

In brief, our experimental strategy for the 2D case complies with the methodology in (Neumann and Stiehl, 1987) for controllable experimentation (see also (Alberti et al., 2018) as well as the in-depth treatise in (Thacker et al., 2008)) proposing the use of a well-defined range of test images with increasing visual complexity. Hence synthetic images of binary line texture (subject to e.g. scaling, orientation, curvilinearity and Gaussian noise) allow for basal performance characterization whereas digital documents with increasing line texture complexity – due to e.g. spatial frequency, orientation, and curvilinearity – do so for task-specific problems. Along the graded range our experiments also reveal the tolerance of certain Gabor kernels to deviation from whatever regularity assumption. As yet no consideration was given to typical degradations in ancient/historical documents such as bleed-through, stains, etc. (except for intensity gradients due to scanning).

As mentioned above, for the sake of both brevity and simplicity we utilized the current OpenCV implementation of the Gabor kernels (see (OpenCV, 2021a) and (Henriksen, 2007)) for our 2D experiments although we found through careful late-minute code scrutiny that neither the normalization of the Gaussian nor the d.c. compensation for the even Gabor kernel (see below) have been implemented. Although the numerical results have a known bias, we decided not to correct for it now in favor of reproducibility by other research groups.

Moreover we have to point out that due to the lacking d.c. compensation the even kernel does not obey the wavelet criterion $\psi(.) = 0$ (Lee, 1996) hence the full complex Gabor transform is not a wavelet transform yet. Apart from that, given that the real even and imaginary odd part resemble scaled differential operators like the seminal ones by e.g. (Hildreth, 1983) and (Canny, 1986) and later on by e.g. (Florack et al., 1993), for the purpose of a full scale-space integration (with degrees-of-freedom like scale/aspect ratio of the Gaussian, local frequency range of the sinusoidal waves, and their orientation) w.r.t. the solution space $S(.)$ from above, both kernels need to be further normalized according to milestone research by (Lindeberg, 1990). To this end of our knowledge no validated and reliable open source tools have been provided in order to fully falsify the theory thru experiments.

As a pragmatic consequence of the lack, in order to constrain the above mentioned full solution space, we adopt the "keep-the-user-in-the-loop" paradigm behind interactive document exploration (see (Pandey et al., 2020) for a recent use case) as follows: Given sets of document images with a minimally required and persistent regularity e.g. in a collection (which is safe to assume), a user is provided with an interactive tool for measuring the prevalent visual texture properties thus tailoring specific sets of Gabor kernels (as feature channels) to the texture detection problem at hand. In this vein of experimentation, the following results for linear, curvilinear and circular textlines have been attained so far (see below).

Since the convolution of a digital document with Gabor kernels alone will not yield the quadrilinear textline representation, post-processing was necessary also in order to visualize the detected lines as briefly described next. First, the gray-value document image as well as the texture parameters such as the height and orientation of the lines are uploaded and convolved with the respective even/odd Gabor kernels. Second, our post-processing entails global/local thresholding on the response maps as well as local extrema detection. The resulting points

are then grouped into lines via a connected component labeling algorithm which is available thru OpenCV (OpenCV, 2021b). The four lines are colored (red/blue as below) and overlaid with the uploaded image. Note that our rough-and-ready post-processing was not a research topic by itself and thus can be varied at each step in order to further improve the results.

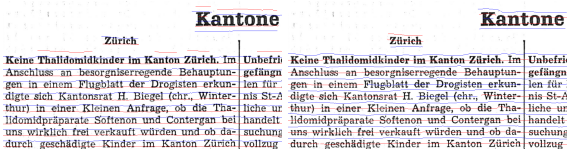
(a) Detected top-/baselines (blue/red) in odd-Gabor response map.

(b) Detected textline/interspace midlines (red/blue) in even-Gabor response map.

Figure 2: Quadrilinear representation of synthetic textlines (height: 10 pixels).

Following our experimental strategy, we first converted the 1D rectangular pulses into 2D straight bars, which can be considered as a regular textline model. Similar to fig. 1 these synthetic textlines have each a height of 10 pixels. Based on this and the given horizontal orientation as pre-knowledge, the Gabor kernels from Equ. 2 and 3 are used with $\lambda = 20, \sigma = 10$, $\gamma = 0.5$ and $\theta = 0$. Both $\lambda$ and $\sigma$ are directly derived from the line height while $\gamma$ is a fixed value hence the solution space $S(.)$ is reduced by three dimensions.

By convolving the synthetic image with even and odd Gabor kernels, the response maps will yield extrema along the quadrilinear lines as shown in fig. 2. Because of the elongation of the (anisotropic) Gabor kernels along the textline, there are still relatively high responses at the end of textlines, which are not suppressed by the thresholding. Note that Gabor-based line end detection is work in progress.



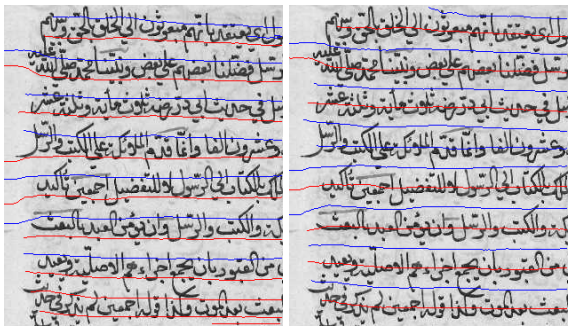

(a) Detected top/baselines in regular text block.

(b) Detected midlines in regular text block.

Figure 3: Quadrilinear representation of newspaper textblock[3].

Applying our approach to real documents faces noise as a result of imperfect imaging barring low resolution and further degradation. Hence efficient thresholding of the response maps as one way to lower the sensitivity to noise is all-important. Fig. 3 depicts our results for a low-noise document with small irregularity due to different font size.

The horizontally aligned anisotropic Gabor kernels used here were parametrized to a line height of 19 pixels thus fitting the text block. Since the word "Kantone" is larger than the textlines in the textblocks below, some false-positives result occur though the kernel setting is quite tolerant against height deviation.

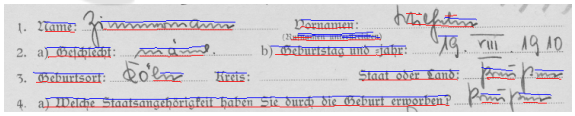


(a) Detected top/baselines in irregular text block.

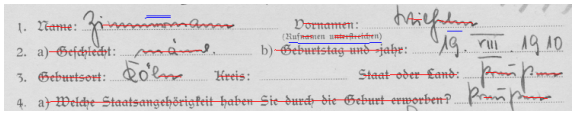
(b) Detected midlines in irregular text block.

Figure 4: Quadrilinear representation of irregular manuscript text block (Islamic Manuscripts, 2021).

In contrast, results for a cropped Arab manuscript with irregularity are given in fig. 4. Despite the particular language and writing style, the lower contrast and some irregularities w.r.t. line height, spacing and orientation, the response maps still expose extrema as in the use cases above. Here the Gabor kernels are tailored to a line height of 21 pixels, due to ascenders/descenders and diacritics, and the results do well approximate a quadrilinear reference systems. Note that spurious detections can easily be suppressed by imposing task-specific geometric constraints.




(a) Detected top/baselines in index card.




(b) Detected textline/interspace midlines in index card.

Figure 5: Quadrilinear representation of index card[4].

A different case of historic documents is a form or index card as shown in fig. 5. Using Gabor kernels tailored to a line height of 11 pixels, the approach is able to detect form fields as well as most of the hand-

[3]Courtesy: Content Conversion Specialists GmbH, Hamburg https://content-conversion.com/

[4]Courtesy: Archive of Universität Hamburg

writing. The increased spacing between the lines prevents the detection of the inter lines with the same Gabor Kernel and requires a different scale. Fitting the Gabor kernel to a line height of 17 pixels will improve the detection of the inter lines, which is shown in fig. 6, but on the other hand the mid lines are not as narrow as in fig. 5, which means bigger gaps between words are connected as shown in the last textline.

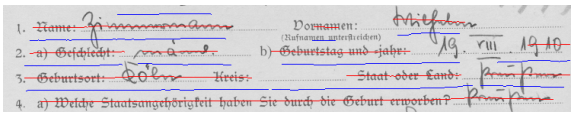
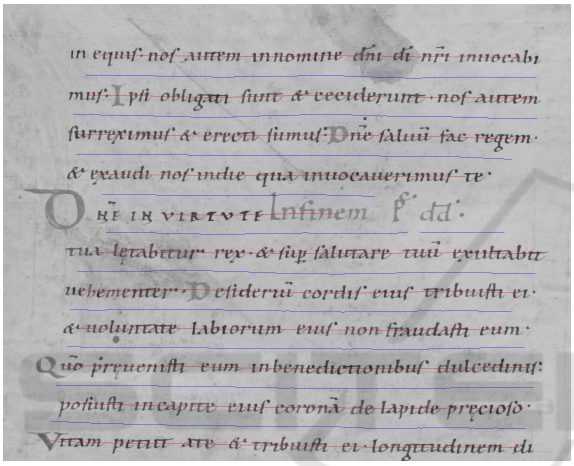
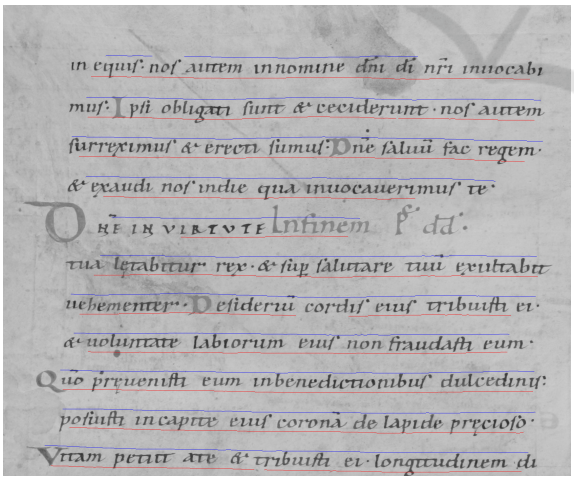


Figure 6: Detected interlines in index card[4].



(a) Detected textline/interspace midlines.



(b) Detected top/baselines.

Figure 7: Quadrilinear representation of a Latin manuscript from DIVA-HisDB (Courtesy: https://diuf.unifr.ch/main/hisdoc/diva-hisdb).

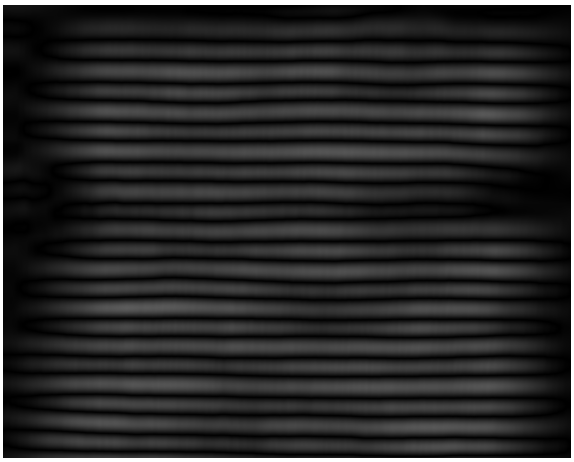
We also tested our approach on some manuscripts from the DIVA-HisDB dataset in comparison to (Mechi et al., 2021, fig. 10). The shown manuscript page in particular stands out w.r.t. an overall difference – or moderate irregularity – in textline height and spacing. As parameter constraint for the Gabor kernels, in our experiment we interactively estimated the page-averaged line height at 67 pixels, which yields a result as shown in fig. 7. Similar to the results from fig. 6, due to the estimated line height the top- and baselines cannot perfectly represent the textline margins but expose tolerance to such irregularity. On the other hand, however, both lines encase descenders and ascenders, which reveals their usability for determining a bounding box in a subsequent processing step.

As mentioned above, our Gabor-based proof-of-concept and the post-processing step include a simple global thresholding to reduce noise. As a result we have some small gaps even though the response map does have local extrema. For illustration purpose fig. 8 displays the response maps of the convolution of data in fig. 7 with even/odd Gabor kernels. Fig. 8 display absolute values to make the extrema more visible, which is why both minima und maxima are shown as high values. The response maps indicate that the gaps are results of the global thresholding, which can be improved with more advanced algorithms.

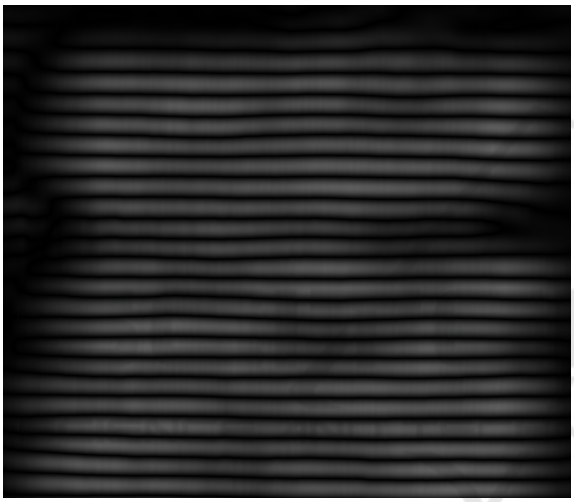
Since 2D Gabor kernels are both selective and sensitive to texture orientation, detection of textlines with varying curvature is not far to seek (fig. 9). However, in the case of curvilinear or even circular textlines, two questions arise: First, how to discretize the angular range and, second, how to match the scale of an anisotropic Gabor kernel to the textline curvature. As shown below, our experiments demonstrate that one set of Gabor kernels is quite tolerant against deviation from textline linearity (fig.9a) but a combination of multiple kernels is required for imposing a quadrilinear reference system on textlines beyond a lower curvature limit. In fig. 9a, with parabola-like textlines having slight curvature of 0.0018, just one even kernel set (for midlines) with an orientation of $\theta = 0.5\pi$ does not suffice.

The midlines are cut-off because the responses were too low and also false-positives are prominent at the line end. Evidently, to detect curvilinear or even circular textlines, a set of Gabor kernels with multiple orientations - depending on the present curvature - is in order.

Our experiments reveal that only three kernels of different orientation are sufficient for fully detecting the mid-lines in fig. 9b. For fusion of the response maps, the arithmetic mean of the responses for each pixel is calculated. However, the responses will be diminished such that the difference between responses

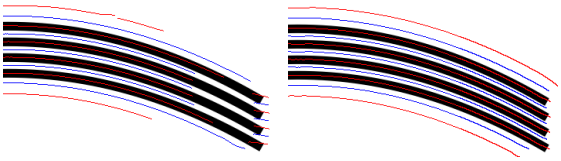


(a) Response map of textline/interspace midlines.



(b) Response map of top/baselines.

Figure 8: Reponse map of the quadrilinear representation of a Latin manuscript from DIVA-HisDB.



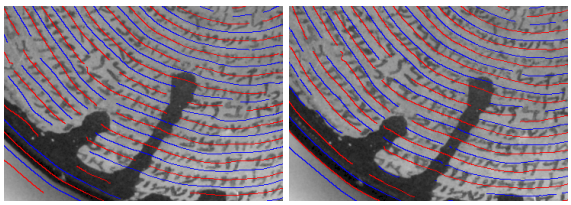
(a) Detected midlines via one even kernel $\theta = 0.5\pi$.

(b) Detected midlines via combination of 3 even kernels $\theta_{1,2,3} = (0.2\pi, 0.5\pi, 0.8\pi)$.

Figure 9: Detection of midlines in synthetic curvilinear text block.

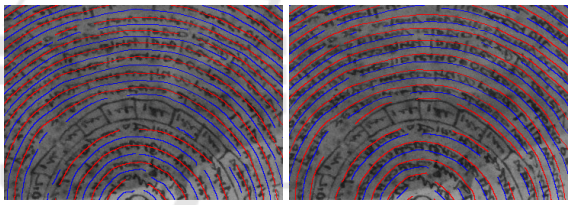
from textlines and noise will be less plainly. To circumvent this effect, which gets worse the more kernels are used, kernels may only contribute to pixels that lay in their respective orientation of detection. Here two assumptions have to be made for our current experimental system: i) the circular textlines have only one center and ii) its coordinates must be prior given. From this center the angle between a pixel and each kernel can be derived to let a kernel only contribute if this angle is within its orientation. Adopting the "keep-the-user-in-the-loop" paradigm, the center is interactively determined and aligned with the center of the cropped image. Ellipse detection using two focal points is ongoing work.

In our experiments 16 kernels are used with orientations equally distributed between $0\pi$ and $(2-\frac{1}{8})\pi$ with a step size of $\frac{1}{8}$. Two exemplary results for circular textlines with a moderate but observable irregularity are presented in fig. 10.



(a) Mid and inter lines with line height of 10 pixels (Tilemahos Efthimiadis, 2010).

(b) Top and base lines with line height of 10 pixels (Tilemahos Efthimiadis, 2010).



(c) Mid and inter lines with line height of 12 pixels (Daderot, 2011).

(d) Top and base lines with line height of 12 pixels (Daderot, 2011).

Figure 10: Detection of epigraphy midlines in bowl images.

Note that in fig. 10a the bleeding glaze of the bowl leads to an irregularity that has not much affected the midline detection whereas in fig. 10c only midlines for the epigraphy are detected while the low responses for the drawn rectangles were removed due to thresholding. The entire set of the quadrilinear line representation for each bowl will be made public via the given footnote link 1. In summary our experiments provide strong evidence of both validity and feasibility of our approach and its proof-of-concept implementation.

## 5 CONCLUSION

In our theoretically well-grounded research we i) defined repetitive textlines with varying properties (e.g. height, spatial frequency, orientation and curvature)

as visual texture in documents, ii) derived an explicit LTI-based model for textlines of varying regularity and their detection via even/odd Gabor kernels with implicit semantics, iii) bridged a specific gap between complex-valued Gabor theory and DAR practice in order to not only detect text(base)lines but to impose a quadrilinear reference system (or "textural stave") as a signage for further computational processes such as Hough transform, textline extraction, word spotting, machine learning, OCR etc., iv) demonstrated the validity of our approach thru controlled experimentation with a variety of documents as a proof-of-concept (see footnote 1) and v) linked our learning-free approach to the "human-in-the-loop-and-control" paradigm.

Needless to say that our current research couldn't reach the top end of the flagpole in DAR practice as pointed out above: Apart from known theoretical blank spots for computationally exploring the solution space solely for the case of texture regularity, in the case of irregularity the role of the Fourier/Gabor phase space – being inherent to the pair of real even and odd imaginary kernels and indicating deviation from textline regularity in the spatial domain – has to be given proper attention in future work. In addition, given the rich quadrilinear text line representation derived so far, Gabor-based texture analysis of text blocks is a next logical step in a processing chain. Moreover, in terms of algorithmic time complexity of multi-scale filter banks, recent GPU hardware progress up to hundreds of TOPS will alleviate computational burden. Taken all together such issues will be part of our research road map to further deepen the transdisciplinary understanding of line texture in documents - in the end probably yielding a theoretically grounded, generic, and bottom-up thus learning-free tool for computation of rich visual representations to be fed into higher-level modules of a fully-fledged DAR system.

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