Measuring parameters of canvas texture from images of paintings obtained in raking light

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Abstract. In this work, the problem of threads counting in images of canvases of paintings is considered. Counting of threads is necessary for measuring canvas density and a number of other parameters used by art historians for dating the artworks. We propose to use raking light in the image acquisition process in order to emphasize canvas texture. We modify and adapt known techniques developed for inspecting fabrics in the textile industry. Three threads counting algorithms based on filtering in the Fourier domain and thresholding techniques are proposed and tested. These algorithms for measuring the canvas density from images taken in raking light are efficient in cases when lead white has been used to create the painting, and the analysis of canvas images acquired in X-rays and transmitted light is ineffective. The results of the experiment show that the accuracy of the proposed threads counting algorithms is comparable to the accuracy of known techniques.

1. Introduction

One of the components of technical and technological research of painting layers is the analysis of canvas support. An important characteristic of canvas used in the attribution of paintings is the density of the fabric in warp and weft directions. To determine the density of the fabric, it is necessary to count the number of threads in the sample. Traditionally, this operation was carried out manually [1].

In the past ten years, automated algorithms for calculating the characteristics of canvases using X-ray images have been developed (see [2-4]). The X-ray images show the “imprint” of the canvas in the ground, and the ground relief corresponding to the threads is clearly visible due to the rather noticeable absorption of radiation by the ground material [4].

In works [5-7], a mathematical model of weave patterns was proposed, and a semi-automatic algorithm was developed for measuring the canvas density from X-ray images based on filtering in the Fourier domain and analyzing the Fourier spectrum peaks. X-ray images of Van Gogh paintings were analyzed. In [7] the authors reported that the best of several spectrum-based algorithms achieved 84% of canvas density measurements within ±0.5 thread/cm and 95% of measurements within ±1 thread/cm in images of 1.8x1.4 cm swatches.

If lead white paint has been used for creating the painting, then X-rays do not provide the required information for analysis. In this case, it is necessary to use images taken in other spectral ranges. To overcome this obstacle, in [3] van der Maaten et al. intended to extend their canvas analysis algorithms
to terahertz images. But they pointed out the impossibility of obtaining a required spatial resolution of canvas images.

To control the density of the fabric in textile production, a number of algorithms based on image analysis methods have been developed [8, 9]. In this work, the transmitted light source was used to illuminate the fabric samples. In [8], the image was fixed by a CCD camera with a 2-megapixel matrix mounted on a microscope. The authors researched woven fabric samples of the size of about 1.2x1.2 cm. Images obtained at a magnification of 10x have a size of 512x384 pixels. To count the number of warp and weft threads, the following algorithm was proposed: (1) the image of the fabric sample is filtered in the Fourier-domain by a filter with a mask in the form of a strip 3 pixels wide along the coordinate axis corresponding to the selected direction (warp or weft); (2) the filtered image is binarized by the adaptive Niblack algorithm [10] with 32x32 pixels window; (3) the number of threads is counted along the baseline. The error obtained in the experiment with 15 fabric samples of three types with different densities does not exceed one percent. In [9], the authors proposed an algorithm comprising the steps of Wiener filtering in the spatial domain and Otsu thresholding method [11]. In the tests, 512x512 pixels images of six fabric samples fixed by CCD camera were used. The error of threads counting in fabric samples of plain structure did not exceed 5%. In paper [12] Aldemir et al. proposed a method for measuring fabric density based on Gabor filters. The method allowed measuring the fabric density with an accuracy of about 90%. Despite the fact that the considered methods developed for analyzing images of fabrics obtained in a transmitted light provide acceptable results, they cannot be applied to analyze painting canvases, because the paint layer of paintings is opaque.

The present work is aimed at developing an efficient automatic technique for measuring painting canvas density from images fixed by a digital camera in a visible spectral band. To solve this problem, we use raking light in the image acquisition process and modify some of the methods presented in the mentioned above works. Distinctive features of the proposed techniques are as follows: (a) using images taken in the raking light; (b) using histograms of the number of threads counted in each row/column of the matrix of the processed image; (c) developed preprocessing and postprocessing procedures; (d) applying the thresholding algorithm based on information criterion.

Shooting in raking light is widely used in technical and technological research of the artworks paint layer and emphasizes the texture of the painting. In this study, shooting in raking light emphasizes the canvas threads in a given direction. The features of canvas paintings generate artifacts in the processed canvas images, which are used to count the number of threads. Using histograms of the number of threads reduces errors caused by artifacts obtained during image processing.

2. Canvas images
In this work, canvas images taken in raking light are used as the source data. This method of image acquisition highlights the threads with the desired spatial orientation. Images are taken from a distance of approximately 30 cm at the position of an illuminator, providing the incidence of light in the range of angles from 10 to 30 degrees relative to the plane of the painting from below, above, left and right. We use Nikon D 7100 digital camera with a Nikon AF-S Micro NIKKOR 40mm 1: 2.8 G lens.

The following features of painting canvases should be noted: threads of different thickness in one sample, variations of thread thickness, presence of contaminants, ground penetration, and thread damages. Uneven tension of the canvas creates a significant curvature of the threads and a significant unevenness of the gaps between the threads. These features of canvas generate artifacts in the processed images. Artifacts create difficulties for applying canvas density measurement methods designed to control fabrics quality in textile production [8, 9]. An image fragment of a canvas dated to 18th century obtained in raking light is shown in Figure 1.

In the next section, three algorithms for counting the number of threads in canvas samples are proposed.

3. Algorithms for counting threads
In this section, three algorithms for counting the number of threads in canvas samples are proposed using the approach developed in [8, 9]. The proposed algorithms are designed using the assumption
that the canvas image has a periodic texture in the warp and weft directions. The main idea of these algorithms is to emphasize texture elements oriented in a certain direction in the sample image, to segment image, and count the segmented objects.

For thresholding filtered image, three algorithms are applied: global Otsu algorithm [11], adaptive Niblack algorithm [10], and the algorithm based on the maximum of the mutual information (MIMax) criterion [13].

Figure 1. An image fragment of a canvas dated to the 18th century: (a) the light falls from above; (b) the light falls from the left.

3.1. Filtering

In [4], a mathematical model of the texture of an X-ray image of the canvas was proposed. The model includes two components: a periodic one, describing the structure of the canvas, and a component describing other X-ray visible layers of the painting (paint layer, stretcher, etc.).

For grayscale images obtained in raking light, we will use a similar model:

\[
I(x) = I_o + a \cdot \sin(2\pi k^T x - \phi(x)) + n(x),
\]

where \( I(x) \) is a grayscale value at image point \( x \) with coordinates \( (x, y) \); \( I_o \) is a shift of grayscale value; \( a \) is an amplitude of the gray level; \( k = (k_1, k_2)^T \) is a vector of wave numbers; \( \phi \) is a phase; \( n(x) \) is a periodic function that simulates weaves of threads. To obtain an image that can be used for counting threads number, it is necessary to perform operations to suppress the component \( n(x) \) of the model (1). The ideal canvas image for counting horizontal threads, created in accordance with the model (1) at \( k_1 = 0 \), \( k_2 = 0.08 \), and \( n = 0 \) is shown in Figure 2.

Figure 2. The ideal canvas image for counting horizontal threads, created using the model (1) at \( k_1 = 0 \), \( k_2 = 0.08 \), and \( n = 0 \).

In the canvas image (see Figure 1), a periodic texture is visible. This texture can be roughly described by the model (1). It seems reasonable to use frequency filtering methods to suppress the component \( n(x) \). As in [8], filtering in the Fourier domain is applied to highlight threads with the desired orientation and spatial frequency range:

\[
I_f(x) = F^{-1} \{ F \{ I(x) \} \cdot M(x) \},
\]
where $I(x)$ is an input image, $I_f(x)$ is filtered image, $F_I$ and $F^{-1}$ are the direct and inverse Fourier transform, and $I_m(x)$ is a filter mask. To select the horizontal threads in the sample image $I(x)$, we use the mask in the form of a strip of size $(H/4+1)\times3$ pixels for warp and $H\times3$ for weft threads. The mask is blurred by a Gaussian filter with a small $\sigma$ value. Here, $H$ is the image height. Before Fourier filtering, operations of histogram equalization and of impulse noise filtering [17] of the input image are performed. Filtering operation is illustrated in Figure 3. In Figure 3 (a) – (c), the sample image obtained in raking light, the result of filtering, and filter mask, are shown.

Next, in the filtered image it is necessary to select objects corresponding to the threads.

3.2. Thresholding
In the filtered image it is necessary to outline objects corresponding to canvas threads. For this purpose, we use three segmentation methods. As mentioned above, three thresholding algorithms are used: the global Otsu algorithm [11], the local Niblack algorithm [10], and an algorithm based on the information criterion [13].

3.2.1. Otsu segmentation
The first one is Otsu global thresholding method [11], which was successfully used in work [9]. The Otsu method imposes a threshold value that minimizes intraclass variance. The method shows good results on images with a bimodal histogram, but in the case of a unimodal histogram, it can give an incorrect result. This method is very fast and does not require parameter tuning. In order to remove small objects appeared after thresholding and capable of distorting the result of thread counting, morphological erosion by a 5x5 square structuring element is performed. Thresholded image after erosion is shown in Figure 3(d).

3.2.2. Niblack segmentation
The second thresholding method we apply to the filtered image of the canvas sample is local adaptive Niblack method. The method is used to determine the threshold value in a sliding window:

$$T_N = m + k_N \sigma_N$$

where $T_N$ is a threshold value, $m$ is the mean value, $\sigma_N$ is the standard deviation of image $I_F$ gray values in a sliding window, $k_N$ is a coefficient. Here, we used a 30x30 sliding window size and $k_N = 0.2$. Thresholded image after erosion by a 5x5 square structuring element is shown in Figure 3(e). The result of the Niblack method depends on the ratio of the size of the sliding window and image texture elements.

3.2.3. Segmentation based on mutual information maximization
Another thresholding algorithm is based on the optimization of information criterion. For segmenting the filtered image, it is preferable to apply an algorithm that would not require parameter settings and is also independent of the gray level histogram shape of the analyzed images. In this paper, we propose to use a method, which allows obtaining the maximum informational similarity between the input and binarized images. Such a method was presented in [13]. The method is based on the criterion of the maximum of the mutual information, which the authors called the “maximum segmented image information thresholding criterion”. In this method, the mutual information is used as a measure of image similarity.

Since the method will use the global threshold value, in order to provide the correct segmentation, the processing of the filtered image $I_f(x)$ is required. For this, an uneven illumination is corrected using the morphological closing operation [14] with a square structuring element of size $11\times11$ pixels. Then, to remove small valleys, a morphological closing operation is performed with a structuring element of size $3\times3$:

$$I_{proc} = \phi_B(\left[\phi_{1B}(I_F) - I_F\right]/\phi_{1B}(I_F)),$$  

(4)
where $I_{\text{proc}}$ is the processed image; $\phi_{3b}$ and $\phi_{11b}$ denote closing operations with square structuring elements of size 3 and 11, respectively; “/” denotes the point-wise division.

**Figure 3.** Illustration of the stages of the thread counting algorithms based on Otsu and Niblack thresholding methods: (a) grayscale image of canvas sample; (b) result of sample image filtering; (c) filter mask; (d) the result of applying Otsu method and erosion operation to the filtered image; (e) the result of applying Niblack method and erosion operation to the filtered image; (f) and (g) - histograms of binary object numbers counted in columns of images (d) and (e), respectively.

Consider the following model of the thresholding system:

$$ I_{\text{Bin}} = T(I_{\text{proc}}, t), $$

where $I_{\text{proc}}$ and $I_{\text{Bin}}$ are the discrete random variables describing the processed image (see formula (4)) and binary image (see (5)); $T$ is a function describing image transformation; $t$ is a threshold value. The variables $I_{\text{proc}}$ and $I_{\text{Bin}}$ are stochastically dependent. Here we present a more simple way of obtaining the optimal threshold value than in paper [13].

Mutual information is determined by the expression [15]:

$$ MI(I_{\text{proc}}; I_{\text{Bin}}) = H(I_{\text{Bin}}) - H(I_{\text{Bin}}|I_{\text{proc}}), $$

where $MI(I_{\text{proc}}; I_{\text{Bin}})$ is the mutual information between images $I_{\text{proc}}$ and $I_{\text{Bin}}$; $H(I_{\text{Bin}})$ is the entropy of image $I_{\text{Bin}}$; $H(I_{\text{Bin}}|I_{\text{proc}})$ is the conditional entropy of $I_{\text{Bin}}$ under the condition that the input of system (5) is the image $I_{\text{proc}}$. Since the output of the system is the binary image, then $H(I_{\text{Bin}}|I_{\text{proc}}) = 0$. In this case, the maximum of (6) is reached at the maximum value of the entropy of the output $H(I_{\text{Bin}})$. Maximum of $H(I_{\text{Bin}})$ is taking place in the case of equal probability of the values 0 and 255 in the binary image $I_{\text{Bin}}$:

$$ P(0) = P(255) = 0.5. $$

(7)

Thereby, the threshold value $t$ in the model (5, 6) must be chosen to satisfy condition (7). This result is consistent with those of other thresholding methods based on entropy criteria (see review [16]).
To remove small artifacts confusing thread counting, after thresholding we use dilation with 3 by 3 structuring element, erosion with 5 by 5 pixels structuring element, and the “Fillhole” operation [14]. A result of applying operations (4) to the filtered image of canvas sample is given in Figure 4(c), the histogram of gray levels obtained from this image is presented in Figure 4(d). Thresholded image after dilation, erosion, and the “Fillhole” operation is shown in Figure 4(e).

3.3. Thread Counting
At the next step, it is necessary to count the number of objects in the binary images corresponding to the threads. In [8], counting the number of threads is performed along a given standard line. In this paper, we propose to use the voting procedure. For this purpose, it is necessary to perform counting of threads in all columns of the image matrix and obtain a histogram. The number of threads will be determined by the maximum of the histogram, which will correspond to the maximum number of votes. Each object is characterized by the presence of brightness transitions from 0 to 255 and from 255 to 0 (with the exception of objects containing pixels in the first and last rows of the image matrix). If the indicated combination of brightness transitions occurs when scanning a matrix column, then the number of objects in the column increases by one. After scanning the column, the number of threads found is recorded in a histogram, which corresponds to a vote for this result. The proposed voting procedure improves the reliability of the result since the features of images of old canvases generate objects of complex shape in binary images (see Figure 3 (d, e) and Figure 4 (e)), which leads to counting errors. Histograms of object numbers counted in binary images produced by the three algorithms described above are shown in Figure 3 (f, g) and Figure 4 (f).

The following section presents the results of testing three algorithms for counting threads in photographs of the canvases of paintings created in the 18th century.

4. Experiment
To evaluate the effectiveness of the described above algorithms, a computational experiment is carried out. The experiment includes two stages. At the first stage, the spatial resolution of the sample images, at which the highest accuracy of counting the threads can be achieved, is determined. At this stage, images with highlighted warp threads are used. In the second step, the three described above algorithms are applied to the images of the canvas samples obtained at the selected optimal spatial resolution. At this stage, images with highlighted both warp and weft threads are used.

In the experiment, fragments of images obtained by photographing six paintings in raking light, directed from below or from above and from left or right are analyzed. Images are fixed at angles of incidence of light ranging from 15 to 30 degrees relative to the plane of the canvas. Three samples are taken from each image of the painting. To estimate the accuracy of the algorithms, the obtained values of the number of threads are compared with the results of counting performed by experts. Then we build histograms of relative error values calculated by the formula:

$$\delta = \frac{N_a - N_e}{N_e},$$

where $\delta$ denotes the value of the relative error of counting the number of threads; $N_a$ is the number of threads in the sample found by the algorithm, $N_e$ is the number of threads counted by the experts.

4.1. Choosing the best spatial resolution of canvas sample images
This stage of the experiment involves 30 samples taken from ten images of canvases. Samples contain from 50 to 110 threads. The width of the canvas samples is in the range from 0.7 to 1.7 cm, and the height is in the range from 4.8 to 8.7 cm. The spatial resolution of the sample images covers a range from 390 to 675 pixels per centimeter. For each sample image, three algorithms are used to calculate warp threads. Thread counting is performed at three values of scale: 1, 0.75, and 0.5. The obtained thread numbers are compared with the results of counting performed by experts, and relative error values (8) are computed. Histograms of errors constructed for the three algorithms are shown in Figures 5-7.
Figure 4. Illustration of the stages of the thread counting algorithm based on the mutual information maximization thresholding method: (a) grayscale image of the canvas sample; (b) result of sample image filtering; (c) the result of correction of uneven illumination; (d) histogram of gray levels of the image shown in figure (c); (e) image (c) after thresholding, dilation, erosion, and the “Fillhole” operation; (f) histogram of binary object numbers counted in columns of image (e).

The results of the experiment obtained in case of natural size of sample images (spatial resolution covers a range from 390 to 675 pix/cm) show that the algorithm based on Otsu thresholding method gives the error within 5% on 70% of samples. For 13% of canvas images, the error exceeds 10%. The algorithm using Niblack method provides 5% error in 60% of cases. For 30% of sample images the error exceeds 10% (see Figure 5). The algorithm based on MIMax thresholding technique shows the error within 5% for 93% of canvas samples and in 3% of experiments the error exceeds 10%.

Figure 5. Histogram of the relative error of counting threads using three algorithms; the spatial resolution is in the range from 390 to 675 pix/cm.

The results obtained in the case when the size of the images is 0.75 from the initial (which corresponds to the spatial resolution from 292.5 to 506.25 pixels per centimeter) show that the algorithm based on Otsu method gives the error within 5% on 63% of samples. For 97% of canvas images, it shows error within 10%. The algorithm using Niblack method provides 5% error in 90% of cases. For 10% of sample images the error exceeds 10% (see Figure 6). The algorithm based on
MIMax thresholding technique shows the error within 5% for 93% of canvas samples and in 100% of experiments the error does not exceed 8%.

Figure 6. Histogram of the thread counting relative error; spatial resolution of the images is in the range from 292.5 to 506.25 pixels per centimeter.

When the image size is reduced to 0.5 from natural (in this case resolution is in the range from 195 to 337.5 pixels per centimeter), the algorithm based on Otsu method shows the error within 5% for 30% of samples. For 50% of canvas images, the error exceeds 10%. The algorithm using Niblack method provides 5% error in 73% of cases. For 20% of sample images the error exceeds 10% (see Figure 9). The algorithm based on MIMax thresholding technique shows the error within 5% for 77% of canvas samples and in 20% of experiments the error exceeds 10%.

Figure 7. Histogram of the thread counting relative error; spatial resolution of the images is in the range from 195 to 337.5 pixels per centimeter.

The experimental results show that the algorithms are effective for images at scale values of 1 and 0.75, which corresponds to the special resolution in the range from 292.5 to 506.25 pixels per centimeter. The thread counting algorithms based on Niblack and MIMax methods show the best accuracy. MIMax-based counting technique appears to be more stable to changing image size, than others.

4.2. Performance evaluating

At this stage of the experiment, the described above algorithms were used to count the warp and weft threads. The counting of warp threads was carried out in images of samples with the spatial resolution in the range from 292.5 to 506.25 pixels per centimeter, which was determined at the first stage of the experiment. Measurements of warp threads number were carried out in 33 images, partially different from those used in the previous step. Figure 8 shows the resulting histogram of relative errors of threads counting. The algorithm based on the local Niblack method showed zero error in 54% of cases, the counting error within 5% was obtained for 90% of the samples, and for 9% of the samples, the
error exceeds 10 percents. The algorithm based on the Otsu method showed zero relative error in counting threads in only 12% of test images, an error of no more than 5% - in 76% of images, and the error of more than 20% - in 15% of images.

Weft threads counting was performed in 45 sample images. The resulting histogram of relative errors of counting the threads is shown in Figure 9.

The algorithm based on the Otsu method calculated the number of threads with the error not exceeding 5% in 4% of sample images, with the error within 10% in 20% of images, and more than 20% in 49% of images. The algorithm based on the local Niblack thresholding method counted the number of threads with zero error in 30% of sample images. The error not exceeding 5% was obtained in 35% of cases, and the error not greater than 10% - in 49% of sample images. The algorithm based on the maximum of the mutual information criterion in 73% of cases showed accuracy within 5%, and in 100% of cases - less than 10%.

In practice, the density of the canvas is measured by experts in the number of threads per unit length in the direction of the warp or weft [14]. When estimating the density of canvases in the direction of the warp threads, the algorithm based on the Otsu method in 92.8% of cases showed the error within 1 thread per centimeter, the algorithm based on the Niblack method – in 83%, and the algorithm based on the mutual information maximization - in 100% of cases. When estimating the canvas density in the direction of weft threads, the algorithm based on the Otsu method always showed the error of more than one thread per centimeter, and the algorithm based on the Niblack method - for 60% of samples. The algorithm based on the maximization of the mutual information criterion in 88% of cases provided the error not exceeding one thread per centimeter.
5. Conclusions
In this work, the problem of threads counting in images of canvases of paintings was considered. We proposed to use canvas images taken in raking light to emphasize the warp and weft threads. We used the known approach based on filtering in the Fourier domain and thresholding techniques. Three threads counting algorithms were modified taking into account the features of images of canvases of paintings. The voting procedure for counting threads was proposed.

To evaluate the effectiveness of the threads counting algorithms, a computational experiment was carried out. The results of the experiment showed that the accuracy of the proposed algorithms is comparable to the accuracy of known techniques. Thread counting algorithm based on the mutual information maximization thresholding technique demonstrated the highest accuracy at various values of the spatial resolution of canvas images.

The future research will be aimed at improving the accuracy of counting weft threads and developing methods for analyzing weave patterns and measuring other parameters of canvases of paintings.

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Acknowledgments
The research was supported in part by the Russian Foundation for Basic Research (grants No 18-07-01385 and No 18-07-01231).