A Probabilistic Approach for Tracking Fibers

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Abstract

This paper describes a combination of an automated image acquisition method and a probabilistic tracking method for analysis of the 3D microstructure of a sheet of paper. A prototype which combines microtomy and light microscopy enables efficient and fully automated digitization of paper samples in high resolution. A particle filter based tracking method then allows to segment individual fibers from the obtained 3D data sets. The capability of accessing the properties of individual fibers enables analysis of e. g. 3D fiber mass distribution, 3D fiber orientation or fiber morphology. Experiments show that the method provides results consistent with the knowledge of paper experts.

1. Introduction

In general, paper is a complex network of fibers, fiber fragments and filler pigments. Every square centimeter of a typical sheet of paper contains approximately 10 000 to 100 000 fibers which build a complex three-dimensional network. The capability of accessing individual fibers or pores and the measurement of their properties allow a deeper insight into the microstructure of paper. For instance, the spatial arrangement of the fibers plays a decisive role in the development of paper strength. In this paper we focus on the reconstruction of the 3D fiber network of a sheet of paper which enables analysis of paper technology relevant topics as 3D fiber orientation, 3D fiber mass distribution, fiber morphology or fiber bonding areas.

To be able to digitally reconstruct the fiber network of a sheet of paper two subsequent steps have to be done. First, the 3D structure of a paper sample has to be digitized and second, individual fibers have to be segmented in the obtained 3D data sets by means of computer vision.

A 3D imaging technique for analysis of the microstructure of a sheet of paper has to fulfill some severely conflicting requirements. First, a resolution of at least in the micron range is required to be able to identify all main paper components and important structure details. Second, to reasonably analyze paper structure in micro scale at least some square millimeters and ideally one square centimeter should be analyzed. Finally, the technique should be applicable in "day-to-day" research on commercial paper samples and investment and operating costs should be moderate.

An extensive review of the 3D imaging literature showed, that there is a wide range of non destructive (CLSM, X-ray microtomography) and destructive (sheet splitting, serial sectioning) techniques available for three dimensional analysis of the micro-structure of materials. Most of them have been applied to paper materials in recent years but none of the methods is able to fulfil all aforementioned requirements. This was the starting point for the development of an episcopic, slice-based, and fully automated approach with an enlarged sample size. Therefore, a prototype was designed and built which is described in Section 2.

After digitization of the 3D paper structure individual fibers have to be identified in the 3D data sets by means of computer vision. Since, the digitization method provides a sequence of images including the cross sections of all fibers in every frame a robust tracking method is required. Visual tracking is an important task in many computer vision applications as e. g. in visual surveillance, human computer interaction, traffic monitoring, augmented reality, sports analysis, etc. Tracking is a challenging problem due to the presence of noise, occlusion, clutter and dynamic changes in the scene. A variety of tracking algorithms have been proposed to overcome these difficulties. They can be roughly classified into two categories: deterministic and probabilistic methods.

Among the deterministic methods are classical template trackers [4], mean-shift trackers [3] and appearance based tracking methods [2] which allow efficient calculation but are sensitive to background clutter and occlusion. Furthermore, there is a huge amount of work on model-based tracking, see e. g. [9, 10].

Probabilistic methods use the state space to model the underlying dynamics of the tracking system. The particle filter, also known as sequential Monte Carlo [1], is the most popular approach. In the computer vision community it has been widely applied to tracking problems where it is also known as Condensation algorithm [5]. The particle filter can be interpreted as a probabilistic search algorithm where a set of particles, each representing one possible state, models the posterior probability representing the current knowledge about the object state.

Particle filters applied for tracking typically use color, contours or appearance models as underlying features. Because for every hypothesized state all features have to be calculated the computational complexity strongly depends on the number of particles [11]. Unfortunately the number of required particles increases exponentially with the dimensionality of the state space.

In this paper we describe an efficient particle filtering method for tracking fiber cross sections through an image sequence. We show how particle filtering provides the necessary tracking robustness and the detection of Maximally Stable Extremal Regions (MSERs) provides the required fiber cross section segmentations per frame.

The outline of the paper is as follows. Section 2 describes the 3D digitization method which provides image sequences representing the 3D structure of a sheet of paper. Section 3 introduces the particle filter framework for tracking the fiber cross sections and outlines how the required segmentations are calculated. Section 4 proves that analyzing the reconstructed fiber networks provides results consistent with the knowledge of paper experts. Finally, Section 5 draws some conclusions and gives an outlook on future work.

2. 3D Digitization

To be able to digitize the 3D structure of a sheet of paper we apply a serial sectioning method based on a hardware prototype. The main part of the prototype is a rotary microtome. Microtomes are precision instruments designed to cut uniformly thin sections of an embedded specimen, e.g. embedded paper samples. The main novelty of the design lies in the rigid attachment of a movable light-optical microscope to the microtome. This allows image acquisition directly on the block surface, a process often referred to as episcopic imaging. This solves the tedious problem of standard microtomy based approaches, where each section has to be prepared manually for image acquisition. In addition, the microscope is fixed on a stage which is placed in front of the microtome and can be moved and positioned with high accuracy in all three dimensions. This moveable stage allows the consecutive scanning of the entire slice area after each cut which is necessary due to the small field-of-view covered by a single image at the high resolution.

The underlying idea of the prototype is to repeatably cut off slices from the embedded paper sample and to acquire a sequence of images per slice area. To enable fully automated digitization each unit of the prototype - microtome, digital camera and stage - can be accessed and controlled by a software interface. The prototype allows digitization of a paper sample with a maximum resolution of $0.26 \times 0.26 \times 0.5 \mu m$. Time need for fully automated digitization of one square centimeter is in the range of 12 hours.

3. Fiber Tracking

In general, fibers within paper are compressed tubes. Figure 1 shows that the cross sections of perpendicularly cut fibers can be identified as homogeneously colored regions with darker boundary and approximately elliptical shape within the images. Because fiber cross sections have the same color as the background, no color information is integrated in the tracking process.

We propose to track the individual fibers through the image sequence based on a particle filter tracking framework. Particle filtering for tracking [5] provides a probabilistic framework, which maintains multiple hypotheses of the current object state and has proven to yield impressively robust tracking results. The probability distribution of the hidden target state $\mathbf{x}_t$ of the tracked object at time step t is estimated using a set of N_P weighted particles $\{x_t^i, w_t^i\}$ with $i = 0...N_P$ and associated measurements z_t^i. Each particle x_t^i simulates the real hidden state of the the object. Using the dynamic model $p(x_t^i|x_{t-1}^i)$ and the observation likelihood $p(z_t^i|x_t^i)$, the posterior distribution $p(\mathbf{x}_t|\mathbf{z}_t)$ is approximated by the finite set of particles

$$w_t^i \propto w_{t-1}^i \frac{p(z_t^i \mid x_t^i) p(x_t^i \mid x_{t-1}^i)}{q(x_t^i \mid x_{t-1}^i, z_t^i)}, \tag{1}$$

where $\sum_{i=1}^{N_p} w_t^i = 1$ is fulfilled and $q(z_t^i|z_{t-1}^i)$ is the proposal distribution to draw particles from. Using the state transition model $p(x_t^i|x_{t-1}^i)$ as proposal distribution leads to the bootstrap filter, where the weights are directly proportional to the observation model $p(z_t^i|x_t^i)$. Finally the posterior density is approximated by

$$p(\mathbf{x}_t|\mathbf{z}_{1:t}) \approx \sum_{i=1}^{N_p} w_t^i x_t^i. \tag{2}$$

To avoid the degeneracy of the particle set, resampling of the weights is done if necessary, see [1] for more details. One of the advantages of particle filtering is that the observation likelihood function and the dynamical model can be easily adapted for different problems without modifying the framework. Also the fusion of several information cues into the likelihood is possible as e. g. shown by [8].

We use a five-dimensional state space for the particle filtering defined by

$$\mathbf{x}_t = [\Delta_r, \Delta_c, S_r, S_c, \Phi] \,, \tag{3}$$

representing similarity transformations with translation (Δ_r, Δ_c), scaling (S_r, S_c) and rotation (Φ). Resampling and particle propagation follow the standard particle filter procedure. The weight update, i. e. the analysis of the current observation, is based on analyzing the Chamfer distance of the estimated transformed shape to an edge map calculated by any edge detection method. We use a post-processed canny-edge result. Finally, the particle set approximates the posteriori probability function estimating the most likely transformation between the frames.

Applying the particle filtering framework allows to robustly track individual fiber cross sections through the sequences providing ellipse representations. Many applications as e. g. the analysis of fiber morphology additionally require an accurate segmentation of the cross sections in every frame. Therefore, after identifying the fiber cross section location in the current frame we apply a Maximally Stable Extremal Region (MSER) detector [6] in the image area defined by a scaled up ellipse. MSERs are one of the best interest point detectors in computer vision as recent publications as e. g. by Mikolajczyk et al. [7] showed. We mainly use the properties of MSERs for segmentation purposes. If MSER detection returns a connected region of appropriate size it is returned as the current fiber cross section segmentation result.

Figure 1 illustrates the tracking result for a single fiber in a sequence of cross sectional images. Although the shape and the location of the fiber cross section change significantly it is robustly tracked through the entire sequence.

The proposed tracking method assigns a unique label to each tracked fiber cross section throughout the entire image sequence. This allows direct access to individual 3D fiber representations and the reconstruction of the 3D fiber network of the digitized paper sample. Figures 2 and 3 show 3D surface renderings of a single segmented fiber and a part of a reconstructed fiber network.

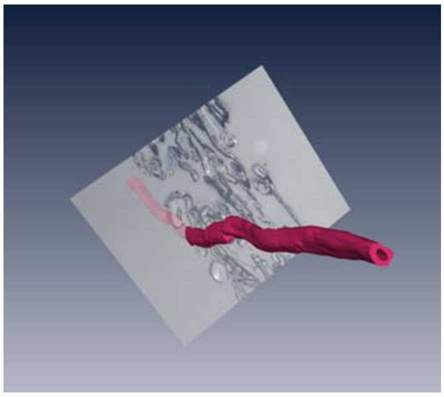


Figure 2: Part of a segmented paper fiber which was identified by the proposed method. The fiber cross section was successfully tracked through 400 frames.

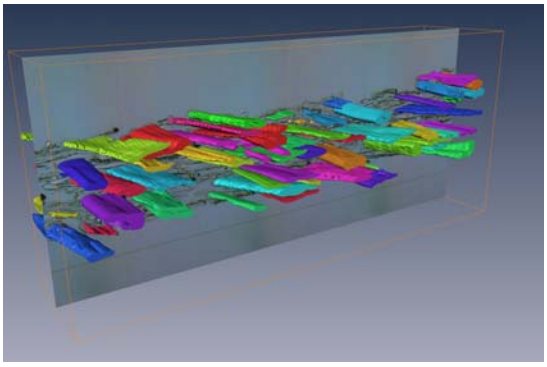


Figure 3: Fiber Network of a paper sample which was reconstructed by the proposed method. Approximately 100 fibers were detected.

4. Experiments

The main focus of the experiments is on proving that analyzing the created 3D fiber network structures yields results consistent with the knowledge of paper experts. Therefore, we analyzed different paper sample properties like 3D fiber orientation, 3D fiber mass distribution and fiber morphology.

We first analyzed the 3D fiber orientation which is represented by the coordinates of the cross sectional centroid. The estimated X-coordinates which represent the movement between the two surfaces of the paper are almost unchanged over the sequence. Therefore, detected fibers seem to be in a predominantly layered arrangement which is consistent with the knowledge of paper experts. We further analyzed the three-dimensional fiber mass distribution which is calculated as the sum of detected fiber voxels along the perpendicular direction to the actual image plane. Again a predominantly layered arrangement was identified.

Finally we analyzed pulp morphology which plays, besides the three-dimensional arrangement of fibers, a crucial role in the development of paper properties. Especially, fiber wall thickness, degree of collapse and fraction of split fibers are important. First attempts were made to classify fibers into collapsed and uncollapsed types by analyzing the fiber wall thickness as described in the work of [12]. Figure 4 shows histograms of fiber wall thickness values for the two different types. As can be seen collapsed fibers have a significantly thinner fiber wall which is again consistent with paper experts knowledge.

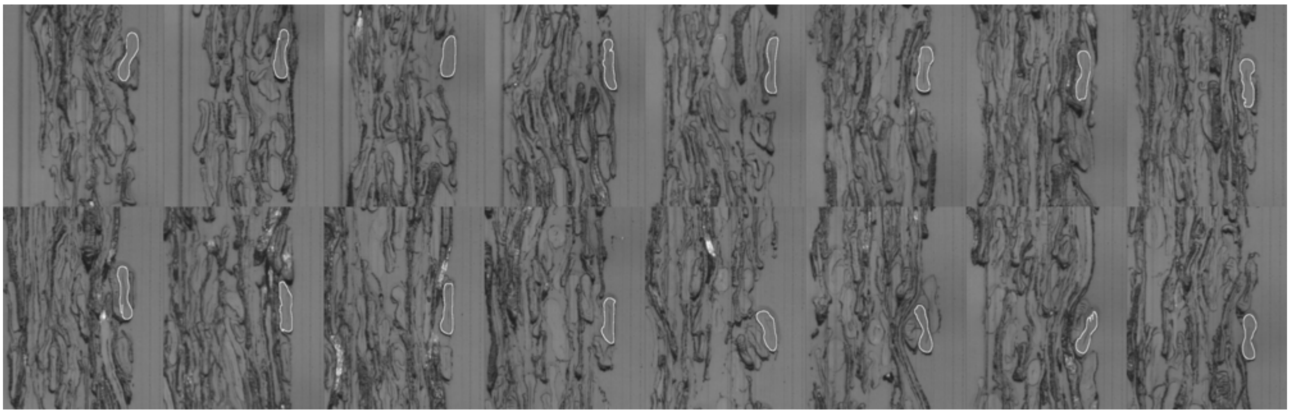
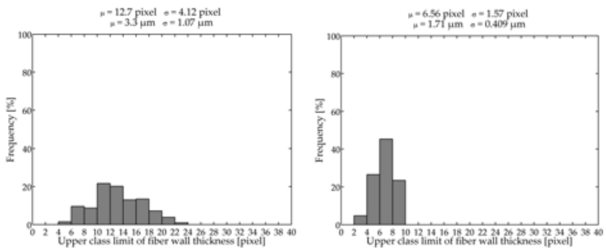


Figure 1: Tracking fiber cross sections through the image sequence. The particle filtering framework enables robust tracking results and MSER detection provides the required fiber cross section segmentations.



(a) Uncollapsed fibers (b) Collapsed fibers

Figure 4: Histograms of the measured local fiber wall thickness for two different classes of fibers.

5. Conclusion

This paper described a method for reconstructing the 3D fiber network of a sheet of paper. An automated microtomy method allows to digitize the 3D structure of a sheet of paper with large sample size, high resolution and moderate operating time and costs. A particle filtering framework then enables to track the fiber cross section robustly through the obtained 3D data sets. First experimental evaluations prove that analyzing the reconstructed 3D fiber network concerning 3D fiber mass distribution, 3D fiber orientation and fiber morphology yields results consistent with the knowledge of paper experts. Future work will focus on analyzing larger paper sample sizes and performing a more detailed evaluation of the influence of the fiber network structure on different paper properties.

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