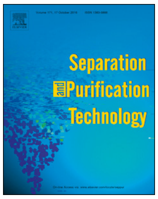
Separation and Purification Technology 207 (2018) 336–343

ELSEVIER

Contents lists available at ScienceDirect

Separation and Purification Technology

journal homepage: www.elsevier.com/locate/seppur



Optical dirt detection for a demand-controlled cleaning of woven filter cloth

Richard-Sebastian Moeller*, Hermann Nirschl

Karlsruhe Institute of Technology, Mechanical Process Engineering and Mechanics, Strasse am Forum 8, 76131 Karlsruhe, Germany

ARTICLE INFO

Keywords:
Closed-loop control
Cleaning
Filter cloth
Hybrid sensor
Smart camera algorithm

ABSTRACT

To cope with ever rising quality demands while in constant transition to flexible product lines, cleaning should be considered an integral part of any process design and processing operation. For many unit operations feasibility has been proven. However, in the cross-sectional technology of solid-liquid separation, progress in hygienic design of filtration equipment did not keep pace. As an answer we propose a closed-loop control for cleaning intensity and present a method to evaluate the cleanliness of any woven filter cloth. The weave's periodicity is evaluated automatically, based on a reported algorithm. By means of image analysis, particle deposits are detected as irregularities on the near-regular weave pattern. Employing background subtraction, we do not rely on overall contrasts in color or brightness between cloth and soiling. If there is a contrast, we reliably find single particles (of 200 μm in our example), as we demonstrate on different color channels of RGB images. The proposed algorithm was implemented in Matlab and executed on a desktop PC in on-line speed. It will enable economical, safe and reliable cleaning of belt filters and filter presses.

1. Motivation

In recent years, the cleanability of machinery and components has attracted ever-growing attention. Unexcelled hygienic demands in the pharmaceutical industry have caused significant cleaning efforts. Any possible savings face consequential costs for faulty products; therefore willingness to tap these is little. In specialty and high purity chemicals, handling lines have to be employed flexibly for different products in order to yield a profit, and the removal of residues and strict separation of batches is essential to sustain quality. This is most obvious in the color and pigment industry, but also in sectors oriented towards private consumers, where competitiveness and innovations rely on high quality standards. Especially in food production consumer protection, product liability, and expectations regarding constant quality and storage life demand for thorough cleanliness. As a cross-sectional technology, solid-liquid filtration concerns all these trades [1,11].

Cleaning and sanitation should be considered an integral part of food process design and food processing operations [10]. Usually food equipment must be cleaned daily after each work shift. However, when different products are processed in the same equipment, cleaning also depends on the frequency of product changes [28]. The most difficult piece of equipment to clean in a filtration device is the filter media [35]. It possesses a large surface area making it susceptible to soil adsorption. The composition of permeable regions and impermeable structures results in a wide range of flow regimes and wall shear stresses, which causes dead zones and thus retains contaminations [30]. This is why the washing of filter media demands such high intensities to reach the hygienically weak spots: Water is being sprayed onto the filter cloths with pressures up to 10 MPa to detach embedded and adhering particles to prevent accumulation [34].

Many guidelines and standards have been published that have increased the hygienic design quality of many components and equipment [8,29,22], but to this day there is no such document concerning filter media. Hence, it is ever necessary that the cleaning of filter media has to be conducted thoroughly.

However, any automated cleaning procedure has to be validated, commonly on a standardized, worst-case model contamination [32]. Afterwards in the field there is usually no control of success of cleaning on the relevant surfaces. Therefore cleaning procedures are intensified by a certain safety coefficient, which increases the consumption of time and resources and thus economic and ecologic costs [9]. To save these, a closed-loop control for cleaning intensity is necessary. This can include adjusting the impact pressure of the jet (via fluid pressure or nozzle distance), the duration or speed of a run, or at least triggering a repeat.

A demand-oriented cleaning method can in fact be prerequisite for the economic installation and operation of an automated cleaning in place system [37]. As a further asset, a monitoring system can prove in every single case that the surfaces observed are actually clean. This renders any modeling of the cleaning procedure—including use of model contaminations—and all assumptions about analogies needless. This can as well be employed to adapt and quickly evaluate

---

* Corresponding author.
E-mail address: richard-sebastian.moeller@kit.edu (R.-S. Moeller).

https://doi.org/10.1016/j.seppur.2018.06.058
Received 17 January 2018; Received in revised form 20 June 2018; Accepted 25 June 2018

automatically any strictly defined cleaning procedure in those cases where regulation demands such a one.

In practice, actual residue detection is limited at last to the accessibility of the relevant surfaces for a sensor unit. In tank cleaning operations feasibility has been proven [21,13]. But still, this method of observing the organic soil's fluorescence in front of a non-fluorescent stainless steel surface is limited in its application. Adapted to a filter cloth cleaning, there are three shortcomings: Illumination and excitation of the soil bases upon ultraviolet light, exposing the cloths to that radiation yields very similar fluorescence, that interfers and superposes the contaminations'. Moreover, the fabric material quickly decays under UV, and in the third place it is unsettled if inorganic soils are detectable as well.

Luckily, woven filter cloths exhibit a nearly regular surface texture, causing dirt to stand out as an irregularity. Even in cases of similar colors of cloth and soil, a difference in brightness and shape remains detectable. However, this apparent regularity in texture is imperfect due to real-world materials, production, handling, ageing, and image acquisition, for example. Still this approach with methods of image analysis, pattern recognition, and anomaly detection can be applied towards a practical solution. The first step is the identification of the weave's dimensions to find congruent domains in the image. Clean regions will exhibit like-distribution of brightness and edges for example; these are calculated in the second step. Finally, possibly not-clean image segments are identified, and the automated decision is made, whether the cloth is clean or not. Thus, we propose an automated dirt detection that needs no prerequisite knowledge about the cloth, the possible soiling, and any color or brightness difference between the two.

2. Approach

2.1. Image analysis

In the textile manufacturing industry defect detection is a common task in quality control. Automated inspection has been a subject of intense research [14,23]. Starting from solid-shade, un-patterned images of a resolution coarser than the repeat, image analysis advanced together with image acquisition and digital processing capabilities [38]. As specific shortcomings in production yield specific defects in the cloth, typical patterns such as broken yarn, warp floats, or oil stains, for example, are supervised and categorized during production [23] for online weave control feedback.

Graphical texture recognition receives attention in other fields, too: Video surveillance and gait analysis [18]exploits temporal patterns; image data compression aims at redundancies in repetitions [17], computer graphics try to synthesize textures from nearly regular natural surfaces [19].

Despite all analogies towards other fields of application, cleaning control for filter cloths differs in its demands. In contrast to loom controlling, categorization of irregularities is of minor concern, instead, we are interested in recognizing smaller structures than just weave repeat or yarn diameter, i.e. dirt particles, which depend on higher resolution images. In computer graphics repetitive tiles can be preprocessed, so that computational demand does not become a burden at runtime. For our cleaning application the execution speed is a key issue, as cloths in the pursued range of square decimeters to square meters per second should be inspected in sub-millimeter accuracy.

2.2. Forward differences of distance matching functions to detect the pattern repeat

The single most important property of a repetitive pattern is the length of its period. To find it, several methods have been proposed. Oh et al. [26] however summarized, that Fourier analysis [20] and co-occurrence matrices [27] are unsatisfactory means to find the length of periodicity, because they yield salient results only for images with large numbers of repetitions at high computational cost. The same has been stated by Chetverikov and Hanbury [4]: "[A detection] window must span several periods of the structure". Even if this is feasible to depict enough periods at once, this comes along with high computational cost, again. Conventional two-dimensional autocorrelation functions yield additional information, such as two-dimensional displacement vectors and actual shape of the texture primitive again comes along with high computational cost [17]. However, they do neither benefit our approach, nor the application on woven filter cloths, since weave repeats can be assumed both rectangular shaped and arranged parallel to the filter apparatus, just as the supervising camera can easily be installed parallel to the filter apparatus.

Oh et al. themselves proposed a distance matching function λ for a one-dimensional image function of length N [26], that can replace the inertia of a co-occurrence matrix and is calculated in shorter time.

$$\lambda(\delta) = \sum_{i=1}^{N-\delta} [g(i) - g(i+\delta)]^2 \tag{1}$$

With δ representing the forward distance, and g the image intensity. Asha et al. improved it through vectorial implementation [2] to receive a single overall row (analogously column) distance matching plot Λ_r.

$$\Lambda_r(\delta) = \sum_{r=1}^{M} \left(\sum_{i=1}^{N} [f(r,i) - f(r,i+\delta)]^2 \right) \tag{2}$$

With M representing the image height, r the rows, N the width, and f the intensity of the 2d-image. In ideal, synthetic images the function value becomes zero at a displacement matching the periodicity p_r. To evaluate real-world, distorted images, Asha et al. made use of forward distance functions $\Delta\Lambda$ on the distance matching plot. These show prominent minima at distances equivalent to the texture's periodicity (Fig. 3). We employ only their horizontal implementation, denoted by subscript r.

$$\Delta\Lambda_r(d) = \sum_{j=1}^{N-d} [\Lambda_r(j) - \Lambda_r(j+d)]^2 \tag{3}$$

We evaluate these by their strongly positive curvature.

As high execution speed is important to us when we want to evaluate images substantially larger than those of the 256 by 256 pixels usually reported [23], we only take a subsample of five to ten randomly chosen rows—and columns, where appropriate—into account. Even in highly particle-contaminated images this yielded reliable results in only one hundredth of time.

For application in filter cloth cleaning, we can assume that the image window is easily aligned with the lattice of the cloth without any disadvantages or technical restrictions. This rather assures the best detection of the rectangular weave pattern, thus yields the smallest tiles and preserves high spatial resolution for subsequent dirt detection. For the tessellation it is unimportant if there is any phase offset towards the intuitive tile texture, as long as they do combine [5]. The same is true for the actual weave pattern, which could be identified [12]. However, for future advancements and improvements this could help constructing finer and more sensitive dirt detectors (see Section 2.6).

2.3. Background subtraction by rolling ball for feature enhancement

For the most precise and sensitive residue detection of particles without a difference in color we interpose a process step of background subtraction. This enhances contrast between noise-like deposits of small particles and the regular-shaped clean yarn. Since neither local plain nor Gaussian weighted average subtraction satisfied in our test cases, we employed grayscale image erosion by the Rolling Ball method, which was inspired by Sternberg [31]: A grayscale image is interpreted as a map of height values. From behind, a ball is rolled over its surface.