International Journal of Computer Information Systems and Industrial Management Applications.
ISSN 2150-7988 Volume 7 (2015) pp. 181-188

Approach for Online Characterization of Bubbles in Liquid by Image Analysis: Application to Oxygen Delignification Process

Mika Liukkonen[1], Heikki Mutikainen[2] , Jari Käyhkö[2], Kari Peltonen[3] and Yrjö Hiltunen[2]

[1] Department of Environmental Science, University of Eastern Finland
P.O. Box 1627, FIN-70211 Kuopio, Finland
mika.liukkonen@uef.fi

[2] Fiber Laboratory, Mikkeli University of Applied Sciences
Vipusenkatu 10, FIN-57200 Savonlinna, Finland

[3] Fiber Technologies Division, Andritz Ltd.,
P.O. Box 500, FIN-48601 Kotka, Finland

***Abstract*: Tiny gas bubbles are used in a number of industrial processes for separating solids from liquids and for facilitating heat and mass transfer between separate phases. Bubble size is known to be one of the important factors affecting the performance of these processes, so it would be useful to be able to monitor its behavior. In this paper, a novel methodology for automated characterization of oxygen dispersion bubbles is presented. The approach is based on analyzing digital images produced by an industrial CMOS camera which is attached to the process by a borescope. The developed methodology for analyzing images offers robustness and fastness which are significant advantages when it comes to online use of the method in real industrial environments. The approach is demonstrated in an oxygen delignification process, which is an important stage of chemical pulping and widely used for lignin removal before bleaching pulp. The results show that online monitoring of oxygen bubble size is possible using the method.**

Keywords: Image analysis, bubble size, oxygen delignification, dispersion, kraft pulping, CMOS camera**.**

I. Introduction

Small bubbles of gas are exploited in many industrial and other processes in order to separate solids from liquids or to smooth the progress of heat and mass transfer between phases. Gas characteristics such as bubble size may have an effect on the process performance and thus provide a way of controlling and optimizing the process. In general, smaller bubbles are favored in treatment techniques, because their surface area-to-volume ratio is high and their bubble density is larger [1]. This leads to more homogeneous heat and mass transfer and therefore more efficient separation of solids.

Oxygen delignification is an essential stage of chemical pulping and widely used for lignin removal before bleaching pulp [2]. Oxygen delignification can be considered as a selective method for removing residual lignin from pulp suspension with oxygen and alkali. Oxygen is mixed into medium-consistency fiber suspension with fluidizing mixers to generate as homogenous three-phase dispersion as possible. After the mixing stage, pulp is transferred into oxygen delignification reactor where delignification reactions occur during a flow-through lasting about one hour.

Efficient gas-liquid mass transfer is important for oxygen delignification [3]. As pulp passes reactor in a plug-flow state, it is extremely necessary to create as homogenous oxygen dispersion as possible in the mixing stage, because efficient contact between oxygen and pulp is crucial for achieving the maximum lignin removal. Mass transfer phenomena in oxygen delignification consist of several individual stages, e.g. oxygen dissolution to water phase, which can limit the rate of the overall process. Oxygen diffusion is naturally slow and oxygen is poorly soluble especially at a delignification stage having a high alkali concentration and high temperature.

Mixing of oxygen into medium-consistency pulp is a very energy-intensive unit operation. It is possible that mixer design, its operation and operation of the whole delignification process could be improved if the bubble size distribution of the oxygen gas could be determined. Moreover, it is suggested that factors such as mixer rotor speed and pulp consistency may affect the bubble size in oxygen delignification [4], so it is presumable that it could be possible to optimize bubble size and thereby achieve a more efficient process, but this necessitates information on the sizes in different conditions. Recent development of camera and illumination technology has made imaging of gas dispersion in oxygen delignification possible, and the development of this kind of imaging method has been described by Mutikainen et. al [5].

Traditionally, optimization of industrial oxygen delignification systems is demanding, because it requires optimization of reaction chemistry, chemical kinetics, and mass transfer rates [3]. Based on the promising results by Mutikainen et al. [4], [5] it is assumed here that digital image data could provide a useful source of information to be used in the characterization and optimization of the oxygen dispersion process. However, manual analysis of a large number of individual images is not feasible in the long run, because it is time-consuming, laborious, and prone to random and systematic errors. Especially the selection of single objects (i.e. bubbles), which has to be performed for each image, is an arduous step in manual image processing. For this reason, algorithms enabling an automatic or semi-automatic processing are particularly useful in characterizing dispersion bubbles [6]. Preferably, the images should be analyzed, not only automatically, but also online to enable efficient monitoring and control of the dispersion process. Such automated online and offline imaging solutions have been suggested for the characterization of ash particles [7], [8] and flocculation [9]–[12], for example.

Processing and analysis of digital image data has become a regular tool in a wide variety of applications [13] – [16]. It has also been shown that machine vision can be useful in the monitoring and control of many industrial processes [17] – [20]. Detection of circular objects like bubbles is a general problem in image analysis, and a widely used method for dealing with round objects is circular Hough transform, which is typically used in many applications to detect, count and characterize dispersion bubbles or other circular objects [6], [21]–[24]. Nonetheless, Hough transform is not very efficient in detecting spatial connectivity [25], which deteriorates its performance in cluttered images, which are quite typically acquired from real industrial processes. Moreover, methods based on Hough transform are often time-consuming, and therefore may not be the best choice for online monitoring and control in a real industrial environment. In addition, it has been proposed that the conventional image analysis methods for measuring bubble size are generally limited in their robustness and applicability in highly turbulent bubbly flows [26] – [27].

Advanced image measurement techniques have been used for characterizing dense bubbly flows [26] - [27]. These flows are usually challenging in terms of image processing because of the wide range of bubble size distribution, inhomogeneity of image background, and the excessive presence of bubble clusters [26]. Karn et al. [26] presented a multi-level approach based on extended H-Minima binarization and a cluster processing algorithm to determine bubble size distribution from images obtained in a turbulent bubbly wake of a ventilated hydrofoil. The same methodology was used successfully for investigating the effect of air injection location on the resulting bubble size distribution in two-turbine blade hydrofoil designs [27]. Nonetheless, compared to oxygen delignification process, in this application the bubble size is approximately ten times larger, and also the images are obtained using a totally different technique (Shadow Image Velocimetry).

Strokina et al. presented an approach for detecting transparent spherical objects based on the detection of Concentric Circular Arrangements (CCA) which are recovered in a hypothesize-optimize-verify framework [25]. It is shown by the authors that this method works efficiently for bubbles having bright ridge edges. Nonetheless, as the authors write, small blob-like bubbles which do not have a clear edge generally remain undetected by the method. In addition, this analysis procedure is reported to last about 14s on a PC with a single core 1.6 GHz CPU, which is acceptable in terms of online monitoring, but may be questionable in terms of fast control.

In this paper, a novel methodology for automated characterization of oxygen dispersion bubbles is presented. The approach is based on analyzing digital images produced by an industrial CMOS camera. The developed methodology for analyzing images is totally different than those used traditionally, and it offers robustness and fastness which are significant advantages when it comes to online use of the method in real industrial environments.

II. Materials and methods

A. Process and measurement equipment

Image data were collected from two imaging assemblies installed to the oxygen delignification stage of a kraft pulp fiber line (See Fig. 1). The first assembly was placed right after the mixer of the 1st oxygen stage (referred to as mixer), whereas the second assembly was installed before the reactor tower of the 1st oxygen stage (referred to as tower).

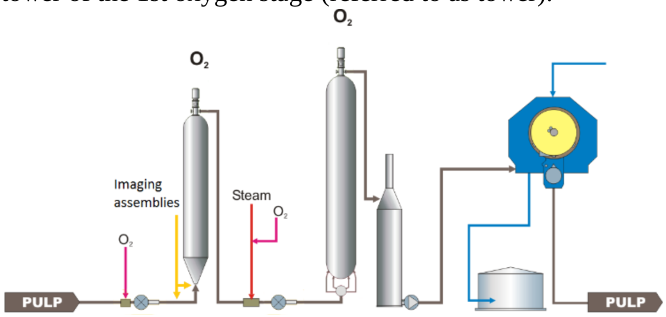


Figure 1. Oxygen stage of the kraft pulp fiber line, in which the two imaging points are marked by yellow arrows.

During the mill experiments, the effect of mixer rotor speed to oxygen gas dispersion was being observed. Image data were collected using a frame rate of 3.5 fps during a few minutes for each selected mixer rotor speed (890, 1000, 1100, 1200, 1300 and 1380 rpm).

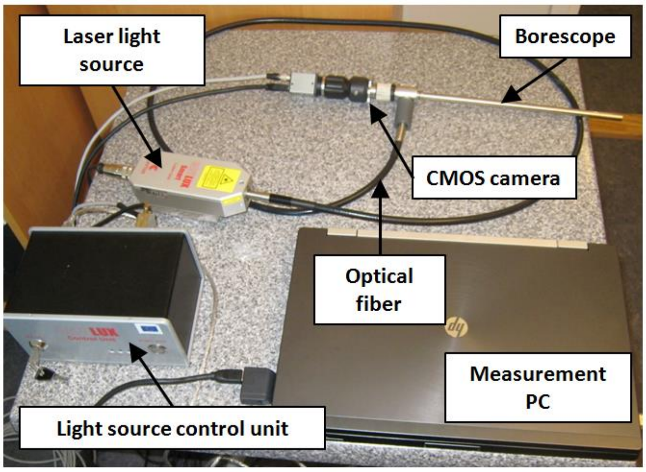
Special equipment is needed to achieve images of sufficient quality from the delignification process. The measurement equipment used for image acquisition and its installation on the kraft pulp fiber line can be seen in Fig. 2. The system includes an industrial CMOS camera (Guppy PRO F-503B, 5 megapixels), a borescope, a lighting unit (Cavilux Smart) connected to the borescope by an optical fiber, and a measurement PC.

B. Image data

The physical size of the collected images was determined visually by placing a focusing grid in front of the window. Picture dimensions were 1.75 x 1.31 mm having a resolution of 2588 x 1940 pixels. Image data were analyzed manually; 10 images from every sampling point were evaluated one by one using a Matlab-based annotating tool. The numbers of images in validation and test sets can be seen in Table 1.

C. Image analysis

The starting point for designing the image analysis methodology for oxygen bubbles was that it should be, not only able to determine bubble sizes, but also online-applicable, relatively fast, and robust. Looking at the problem from this offset, a novel computational, online applicable methodology for characterizing oxygen dispersion bubbles in digital images was developed.



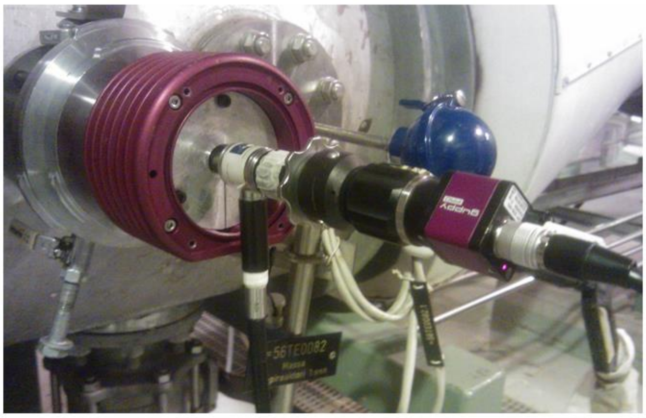


Figure 2. Measurement equipment (up) and installation on the kraft pulp fiber line (down).

Table 1. Description of data used in validation and final tests.

	Validation data set	**Entire data set**
Mixer set	Number of images	Number of images
890 rpm	10	208
1000 rpm	10	198
1100 rpm	10	178
1200 rpm	10	198
1300 rpm	10	184
1380 rpm	10	212
Tower set		
890 rpm	10	198
1000 rpm	10	191
1100 rpm	10	134
1200 rpm	10	140
1300 rpm	10	177
1380 rpm	10	167
TOTAL	**120**	**2 185**

The procedure is based on analyzing digital images produced by an industrial CMOS camera. The method involves the following main stages:

1. Pre-processing
2. Binarization and morphological operations
3. Analysis

Original images produced by the camera are extremely challenging in terms of reliable analysis (See Fig. 3 left), for which thorough pre-processing is needed. Pre-processing of bubble images constitutes a 5-stage procedure which includes cropping, taking an image complement, intensity adjustment, 2-D adaptive noise removal filtering, and contrast-limited adaptive histogram equalization. Some pre-processing stages can be seen in Fig. 3.

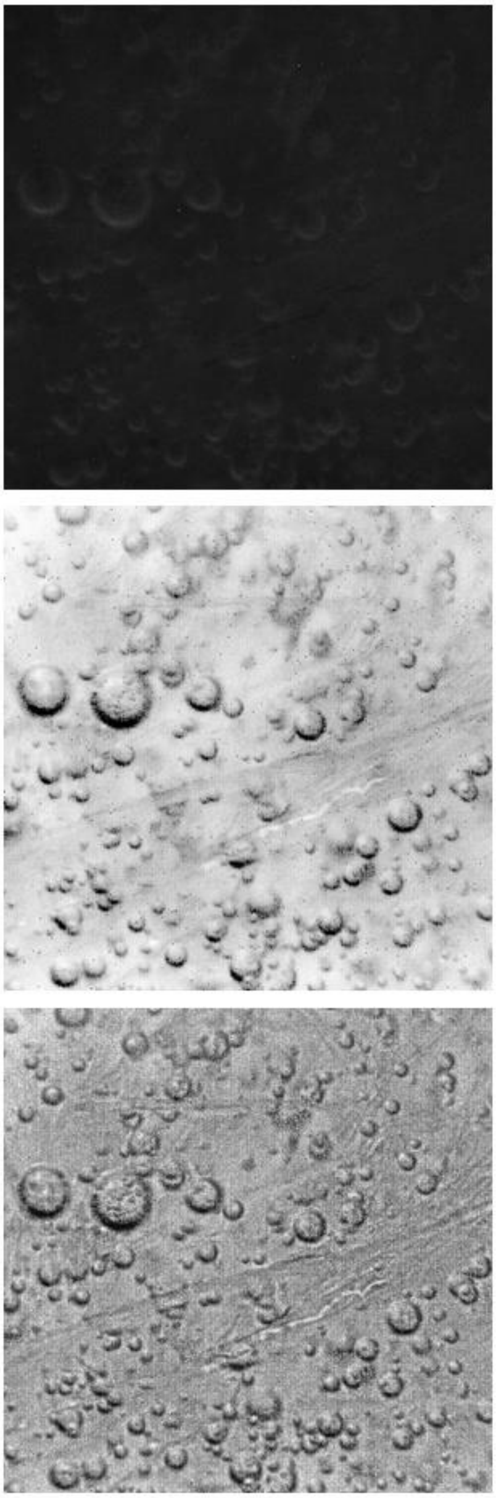


Figure 3. Preprocessing stages: an original (cropped) image on the top, image after intensity adjustment and 2-D noise removal filtering in the middle, and image after contrast-limited adaptive histogram equalization at the bottom.

Binarization can be performed either using an automatically defined or a fixed threshold [22], [28]. The binary image is eventually created using a 4-connected neighborhood.

Connected components, or objects, can be identified from the binary image using the defined neighborhood. At this stage, as we wish to analyze oxygen bubbles, which are assumed to be circular in shape, we are primarily interested in objects having a round form. Therefore, the detected objects can be filtered by their eccentricity, which is the ratio of the distance between the foci of an ellipse surrounding the object and its major axis length (See Fig. 4). In this particular case, eccentricity limit of 0.9 was used in filtering objects. After this, the diameters and volumes of the detected objects can be calculated as pixels and transformed to desired units if the pixel size is known. In this case, the resolution is 1480 pixels per millimeter.

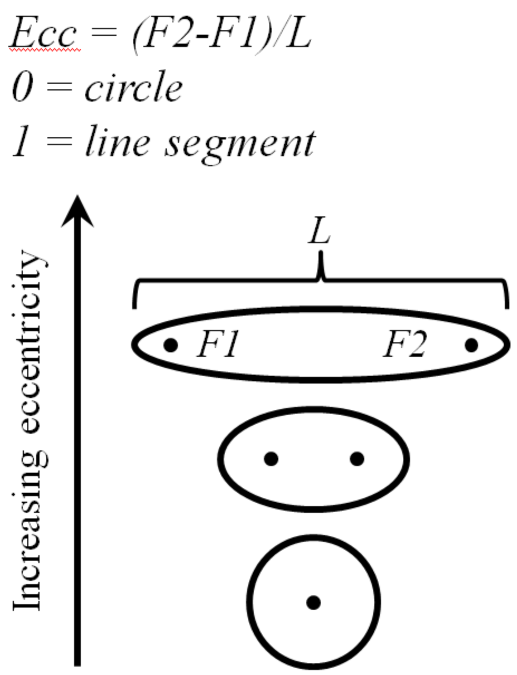


Figure 4. Definition of eccentricity which is used to detect round objects in binary images.

An example of detecting bubbles in a digital image is presented in Fig. 5. As can be seen, the method is able to detect both large and small bubbles. On the other hand, it can be noted that bubbles which are clearly separated from each other are detected most efficiently, whereas overlapping bubbles may not be detected by the method.

The whole procedure of analyzing a single image takes about four seconds per image on a PC having a double core 1.9 GHz CPU and Windows 8 operating system, which is acceptable in terms of controlling the process.

III. Results

A. Validation of the method

The image analysis methodology was first applied to the set of images evaluated one by one using the manual procedure. The results gained by the analysis method were compared to those based on manual analysis. Results from validating the methodology can be seen in Figs. 6 (mixer set) and 7 (tower set). Each point in the graph represents the average values calculated from ten images, so that the red crosses illustrate the results from the analyses performed by naked eye, and the blue circles represent the values computed by the image analysis procedure. It can be seen that the correlation between the computed and manually estimated values is excellent, with the exception of the largest diameter in the mixer data set.

B. Case application

Next, the entire image data sets acquired from the oxygen delignification stage of the kraft pulp fiber line were analyzed using the approach. Results from analyzing the entire sets can be seen in Figs. 8 and 9. In general, it seems that the average bubble diameter decreases with the increasing rotor speed in both sampling points. However, it is also easy to see that there is large variation in the diameter, especially when low rotor speed is used. Moreover, it seems that there is some sort of cyclic behavior which is time-dependent and can be detected at all rotor speeds.

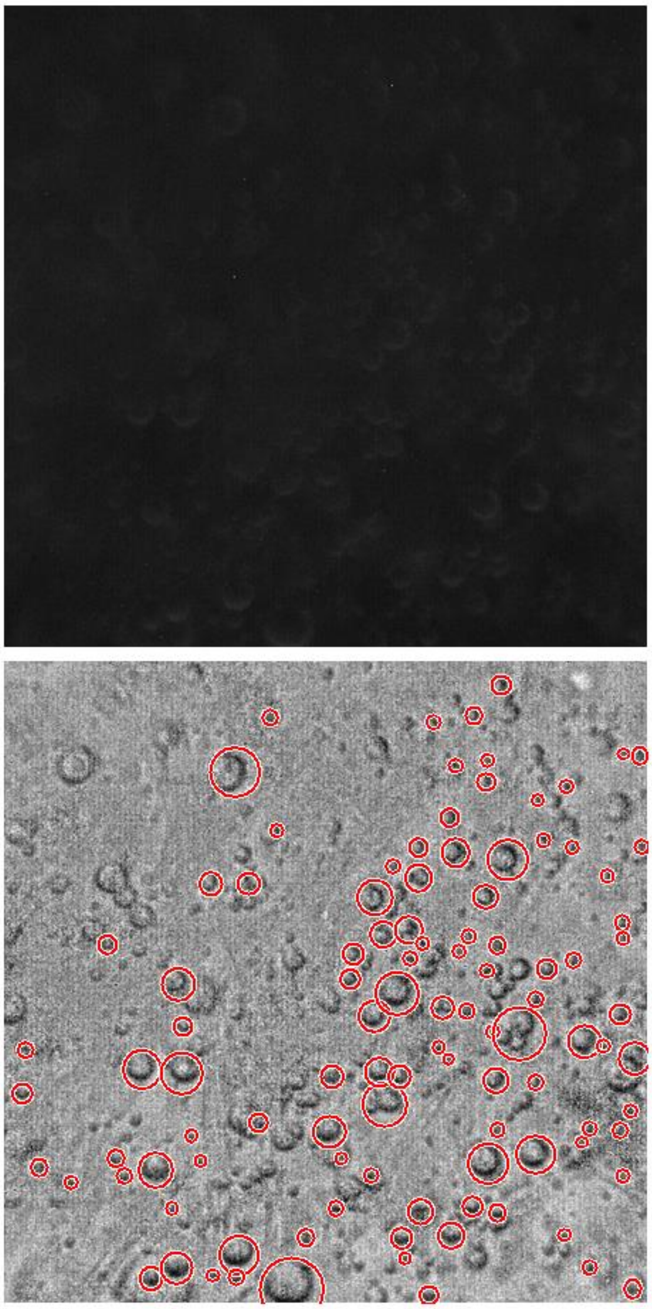


Figure 5. Example of a cropped original image having 1480 x 1480 pixels (up) and a pre-processed image (down) in which the detected bubbles are shown by red circles.

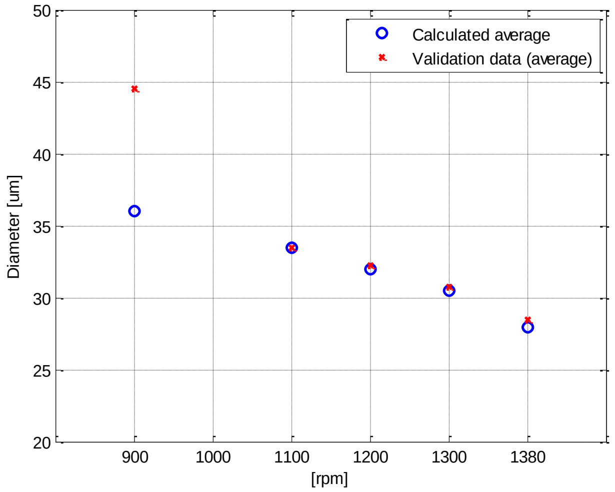


Figure 6. Comparison of averages calculated by the image analysis procedure to validation data (mixer data set)

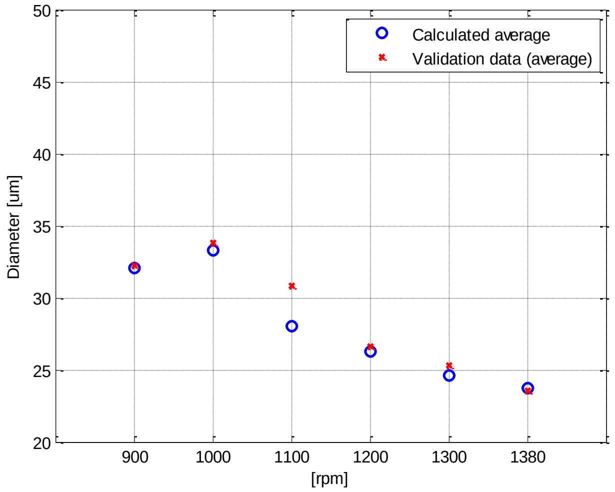


Figure 7. Comparison of averages calculated by the image analysis procedure to validation data (tower data set)

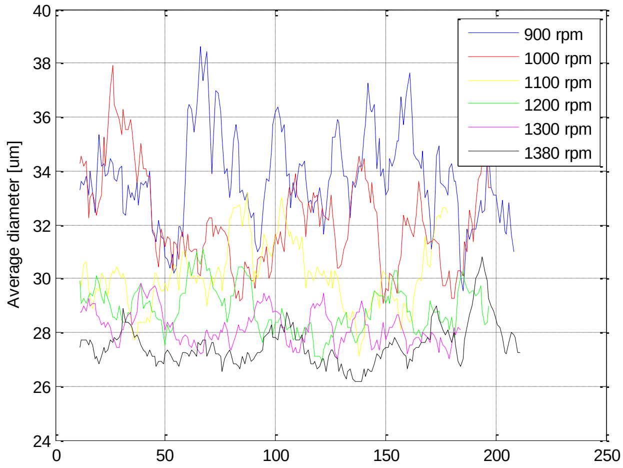


Figure 8. Results from analyzing the entire mixer image set, using moving averages of ten images.

The average bubble diameter (calculated using the entire image set) versus the rotor speed can be seen in Fig. 10. It can be seen that the behavior of the bubble diameter is quite similar in both sampling points. The standard deviations of the calculated results can be seen in Table 2.

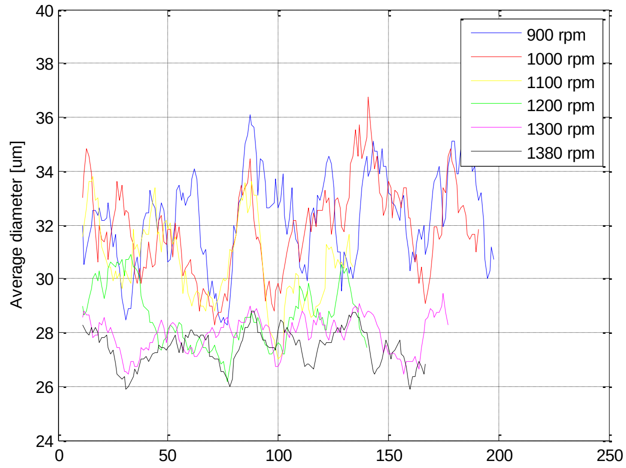


Figure 9. Results from analyzing the entire tower image set, using moving averages of ten images.

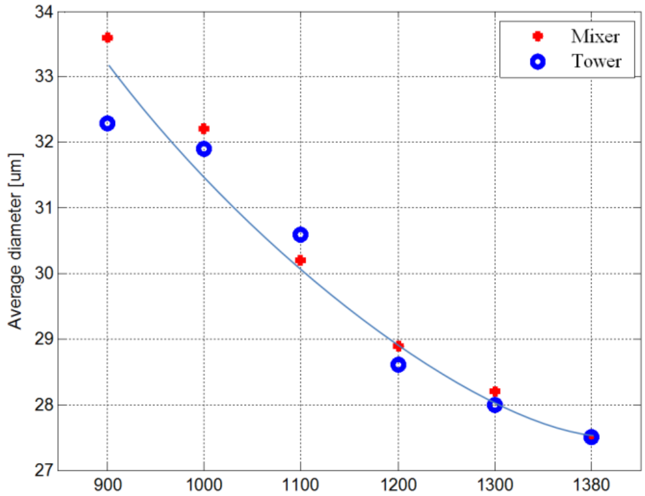


Figure 10. Average diameter of bubbles vs. the mixer speed using the averages calculated from all images.

Table 2. . Deviation of calculated results (all images).

Rotor speed [rpm]	Mixer		Tower	
	STD1*	STD2**	STD1*	STD2**
900	18.3	6.90	16.4	5.49
1000	16.4	5.78	15.5	5.48
1100	13.8	3.85	14.8	4.55
1200	12.0	2.98	11.6	2.91
1300	11.6	2.37	10.9	2.27
1380	10.5	2.44	10.4	2.02

*STD1 = average image-specific standard deviation [μm]

**STD2 = standard deviation of image-specific averages [μm]

C. Software application for analyzing dispersion images

Manual processing of dispersion images is laborious and time-consuming. *OBSeeker* is a specially designed piece of analysis software that can be used to automate the analysis of oxygen bubble characteristics. The analysis procedure used by the OBSeeker is based on the methodology presented in this paper. The standalone software has been coded using the Matlab-software platform (Mathworks, Natick, MA, USA). The calculated image-specific averages and deviations of bubble diameters and volumes can be seen on the screen (See Fig. 11). In addition, the system outputs information on both image-specific averages and the characteristics of individual bubbles to separate xls-files.

The present version of the software is designed for offline use only, so that a set of images has to be first collected during experiments, after which the collected images can be analyzed by the software in a reasonable time. On the other hand, it would be possible to create an online working solution as well by decreasing the sampling rate so that the analysis could be performed in the meantime of taking the images.

IV. Discussion

Oxygen delignification is an essential stage of chemical pulping process, and it would be useful to optimize the oxygen gas dispersion during the process, because this would make it possible to make the delignification process more efficient. It is suggested that factors such as mixer rotor speed may affect the bubble size in oxygen delignification, so it is presumable that it could be possible to optimize bubble size and to improve the efficiency of the process, but more information on the bubble characteristics in different conditions is required to achieve this. Recent development of camera and illumination technology has made imaging of gas dispersion in oxygen delignification possible, and digital image data can potentially be used for process improvement through bubble characterization. Monitoring of oxygen delignification is extremely challenging, however, and highly specialized image analysis techniques have to be used.

As it is shown here, it is possible to estimate the size of oxygen bubbles in the delignification process by using digital image data. Monitoring the bubble size is useful, because, in theory, smaller bubbles enable more homogeneous heat and mass transfer and therefore more efficient separation of solids. Based on the results it seems that there is a clear dependence between the mixer rotor speed and bubble size. In this case it seems that increasing the mixer rotor speed produces smaller oxygen bubbles, so the general conclusion would be to increase the mixing rate as high as possible. However, this might pose some other problems and might not be economical, so it would be interesting to investigate where the realistic limit in increasing the rotor speed actually is.

In this study, the determined bubble diameters vary from 20 to 45 micrometers. As a matter of fact, in the literature there is no experimental information on the oxygen bubble size in mill scale oxygen delignification process. Strokina et al. estimated bubble radiuses of up to 0.5 mm for the majority of bubbles in a pilot process [25]. Moreover, Ishkintana and Bennington noticed in their laboratory experiments that the bubble size increased with suspension (fiber) concentration for a given gas flow rate [3], but their laboratory installation produced much larger bubbles than those evaluated in this study. Rewatkar and Bennington concluded that increasing rotor speed improves gas-liquid mass transfer and increases the energy transmitted to the pulp suspension, which increases turbulence intensity and thereby decreases bubble size [29]. This is consistent with the results of this study. As the next step, it would be interesting to find out what the optimal bubble size actually is for efficient lignin removal in different type of oxygen delignification processes.

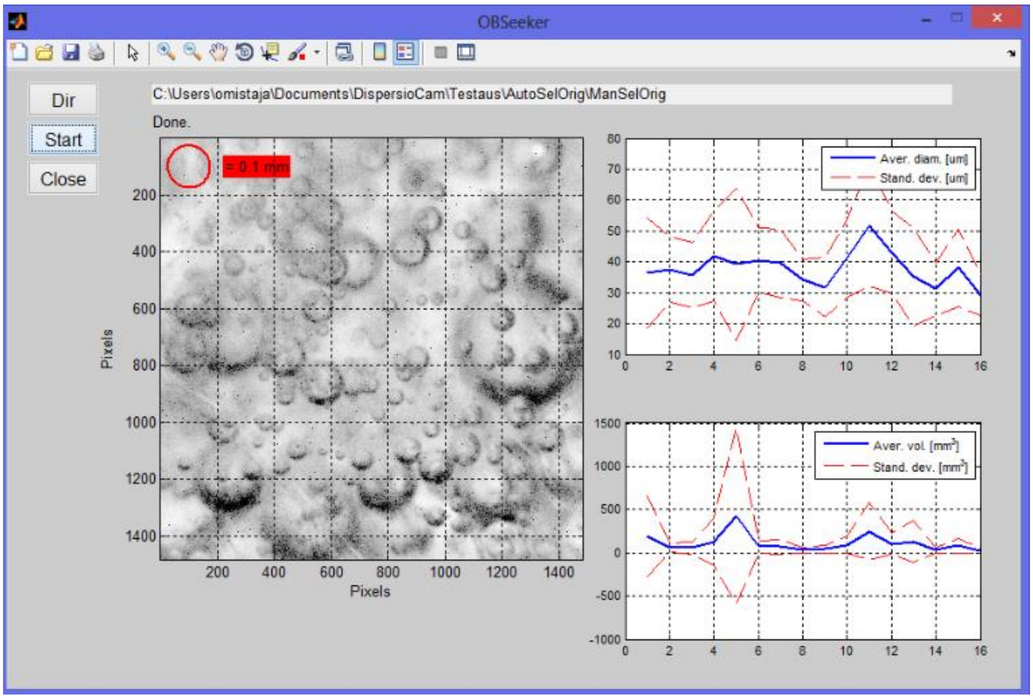


Figure 11. GUI of *OBSeeker* software for calculating oxygen bubble characteristics in a delignification process.

What is more, it is presumable that, in addition to mixer rotor speed, also other variables such as oxygen concentration, pH value, the type of wood used and the amount and nature of dissolved substances in the pulp have their own role in the oxygen delignification process. Therefore, comparison between bubble size and other process measurements could potentially produce valuable information on the behavior of the process. This is another important future consideration, because connecting information on the prevailing process condition with experimental information on bubble size would create a totally new approach for improving the efficiency of delignification process. One single line can nowadays produce five thousand tons dry pulp in a single day, so even small improvements in the process may yield big economical impacts. Mixing of oxygen to pulp does not only consume a lot of energy, but it may also have a decreasing effect on the physical properties of the pulp. That is why it would be economically beneficial to minimize the energy used for mixing the oxygen, but at the same time to guarantee by an online measurement that the quality of oxygen dispersion remains in an acceptable level.

In summary, based on the results it can be suggested that digital image data are useful in characterizing and optimizing the oxygen delignification process. The advantages of the method are robustness and fastness, which are properties that make the method very suitable for online monitoring in a real process. Furthermore, addition of new information such as oxygen concentration and other process measurements could make it possible to create more exact models and to even design a novel control strategy.

V. Conclusions

As oxygen delignification is an essential stage of chemical pulping, it is useful to be able to characterize its condition and behavior. Recent development of camera and illumination technology has made imaging of gas dispersion in oxygen delignification possible. Automated processing is the most reasonable option to characterize dispersion bubbles using digital images. In terms of efficient monitoring and control of the delignification, the images should be analyzed, not only automatically, but also online. The analysis methodology and software presented here provides a practical and flexible way of monitoring the bubble size in oxygen delignification online. The main conclusion to be reached here is that it is possible to estimate the size of oxygen bubbles in this process by using digital image data. Furthermore, it seems that there is a clear dependence between the mixer rotor speed and bubble size, and, in theory, a more economical process can be achieved by optimizing the mixing rate.

Acknowledgment

The research was carried out in the *PulpVision* (Image Processing and Analysis Methods for Pulp Process Measurements) project funded by the Finnish Funding Agency for Innovation (Tekes), the European Regional Development Fund (ERDF) of the European Union, and the participating companies.

References

[1] S.E. Burns, S. Yiacoumi, C. Tsouris. "Microbubble generation for environmental and industrial separations", *Separation and Purification Technology*, 11(3), pp. 221-232, 1997.

[2] Y. Ji, M.C.Wheeler, A. van Heiningen. "Oxygen delignification kinetics: CSTR and batch reactor comparison", *AIChE Journal*, 53(10), pp. 2681-2687, 2007.

[3] L.K. Ishkintana, C.P.J. Bennington. "Bubble Shape, Gas Flow and Gas–Liquid Mass Transfer in Pulp Fibre Suspensions", *The Canadian Journal of Chemical Engineering*, 88, pp. 322-328, 2010.

[4] H. Mutikainen, K. Peltonen, T. Tirri, J. Käyhkö. "Characterisation of oxygen dispersion in medium-consistency pulp mixing", *Appita Journal*, 67, pp. 37-42, 2014.

[5] H. Mutikainen, K. Peltonen, O. Pikka, J. Käyhkö. "Characterization of Oxygen Dispersion in Delignification Process". In *Proc. International Pulp Bleaching Conference*, pp. 51-56, 2014.

[6] E. Galindo, C. P. Larralde-Corona, T. Brito, M. S. Córdova-Aguilar, B. Taboada, L. Vega-Alvarado, G. Corkidi. "Development of advanced image analysis techniques for the in situ characterization of multiphase dispersions occurring in bioreactors", *Journal of Biotechnology*, 116(3), pp. 261-270, 2005.

[7] M. Liukkonen, J. Huhtinen, E. Hälikkä, T. Hiltunen, Y. Hiltunen. "Low-cost Online System for Detecting Unburned Fuel in a Large Industrial Biomass-fired Boiler", *Renewable Energy & Power Quality Journal*, 10, article 310, 2012.

[8] M. Liukkonen, J. Huhtinen, T. Hiltunen, E. Hälikkä, Y. Hiltunen. "Low-cost camera system for online estimation of grain size in fluidized bed". In *IFAC papers online*, *Proc. Mathmod 2012 – 7th Vienna International Conference on Mathematical Modelling*, Vol. 7, Part 1, pp. 964-967, 2013.

[9] R. K. Chakraborti, J. F. Atkinson, J. E. van Benschoten. "Characterization of alum floc by image analysis", *Environmental Science & Technology*, 34, pp. 3969-3976, 2000.

[10] P. Juntunen, M. Liukkonen, M. Lehtola, Y. Hiltunen. "Characterization of Alum Floc in Water Treatment by Image Analysis and Modeling", *Cogent Engineering*, 1(1), article 944767, 2014.

[11] Y. G. Perez, S. G. F. Leite, M. A. Z. Coelho. "Activated sludge morphology characterization through an image analysis procedure", *Brazilian Journal of Chemical Engineering*, 23, pp. 319-330, 2006.

[12] Y. Wang, J. Lu, B. Du, B. Shi, D. Wang. "Fractal analysis of polyferric chloride-humic acid (PFC-HA) flocs in different topological spaces", *Journal of Environmental Sciences*, 21, pp. 41-48, 2009.

[13] S. Castelo-Quispe, J. D. Banda-Tapia, M. N. López-Paredes, D. Barrios-Aranibar, R. Patiño-Escarcina. "Optimization of Brazil-Nuts Classification Process through Automation using Colour Spaces in Computer Vision", *International Journal of Computer Information Systems and Industrial Management Applications*, 5, pp. 623-630, 2013.

[14] H. D. Duong, D. D. Nguyen, L. T. Ngo, D. T. Tinh. "An Improvement of Type-2 Fuzzy Clustering Algorithm for

Visual Fire Detection", *International Journal of Computer Information Systems and Industrial Management Applications*, 5, pp. 235-242, 2013.

[15] S. A. Lashari, R. Ibrahim, N. Senan. "Fuzzy Soft Set based Classification for Mammogram Images", *International Journal of Computer Information Systems and Industrial Management Applications*, 7, pp. 066-073, 2015.

[16] F. Tahir, M. U. Akram, M. Abbas, A. A. Khan. "Detection of Laser Marks from Retinal Images for Improved Diagnosis of Diabetic Retinopathy", *International Journal of Computer Information Systems and Industrial Management Applications*, 7, pp. 131-138, 2015.

[17] S.H. Choi, J.P. Yun, K. Koo, S.W. Kim. "Localizing slab identification numbers in factory scene images", *Expert Systems with Applications*, 39(9), pp. 7621-7636, 2012.

[18] H.-D. Lin, S. W. Chiu. "Flaw detection of domed surfaces in LED packages by machine vision system", *Expert Systems with Applications*, 38(12), pp. 15208-15216, 2011.

[19] J.P. Papa, R.Y.M. Nakamura, V.H.C. de Albuquerque, A.X. Falcão, J.M.R.S. Tavares. "Computer techniques towards the automatic characterization of graphite particles in metallographic images of industrial materials", *Expert Systems with Applications*, 40(2), pp. 590-597, 2013.

[20] M.O. Rahman, A. Hussain, E. Scavino, H. Basri, M.A. Hannan. "Intelligent computer vision system for segregating recyclable waste papers", *Expert Systems with Applications*, 38(8), pp. 10398-10407, 2011.

[21] L. Pan, W.-S. Chu, J. Saragih, F. de la Torre, M. Xie. "Fast and robust circular object detection with probabilistic pairwise voting", *IEEE Signal Processing Letters*, 18(11), pp. 639-642, 2011.

[22] J. C. Russ. *The Image Processing Handbook*, 6th ed., CRC Press, Boca Raton, 2011.

[23] B. Taboada, L. Vega-Alvarado, M. S. Córdova-Aguilar, E. Galindo, G. Corkidi. "Semi-automatic image analysis methodology for the segmentation of bubbles and drops in complex dispersions occurring in bioreactors", *Experiments in Fluids*, 41, pp. 383-392, 2006.

[24] L. Vega-Alvarado, B. Taboada, E. Galindo, G. Corkidi. "Hough transform based method for air bubbles and oil drops segmentation in dispersions occurring in stirred bioreactors". In *Proc. 25th Annual Int. Conf. of IEEE Eng. in Medicine and Biology Society*, 2003.

[25] N. Strokina, J. Matas, T. Eerola, L. Lensu, H. Kälviäinen. "Detection of Bubbles as Concentric Circular Arrangements". In *Proc. the 21st International Conference on Pattern Recognition*, pp. 2655-2659, 2012.

[26] A. Karn, C. Ellis, R. Arndt, J. Hong. "An integrative image measurement technique for dense bubbly flows with a wide size distribution", *Chemical Engineering Science*, 122, pp. 240-249, 2015.

[27] A. Karn, C. R. Ellis, C. Milliren, J. Hong, D. Scott, R. E. A. Arndt, J. S. Gulliver. "Bubble size characteristics in the wake of ventilated hydrofoils with two aeration configurations", *International Journal of Fluid Machinery and Systems*, 8(2), pp. 73-84, 2015.

[28] N. Otsu. "A Threshold Selection Method from Gray-Level Histograms", *IEEE Transactions on Systems, Man, and Cybernetics*, 9(1), pp. 62-66, 1979.

[29] V.B. Rewatkar, C.P.J. Bennington. "Gas-Liquid Mass Transfer in Low- and Medium-Consistency Pulp Suspensions", *The Canadian Journal of Chemical Engineering*, 78, pp. 504-512, 2000.

Author Biographies

Mika Liukkonen, born in Jyväskylä, Finland, August 22, 1979, graduated from the University of Oulu, Finland, as M.Sc. (eng., Process technology) in 2007 and from the University of Eastern Finland as PhD (Environmental technology) in 2010. His main research interests include analysis and modeling of measurement and other data, decision support and monitoring systems, advanced software applications, and advanced measurement systems. Research covers a variety of industrial environments including water and wastewater treatment, energy, pulp and paper, mining industries and electronics production.

Heikki Mutikainen, born in Kotka, June 7, 1984, graduated from the Lappeenranta University of Technology as M. Sc. (Chemical engineering) in 2011. Project researcher in PulpVision-project during 2011 – 2014, research activities consisting development of new imaging based measurement methods for industrial cases from pulp and paper industry. Project researcher in Flash-project 2014-2015, research activities connected to measurement of rapid phenomena in industrial mixing applications. Working for Andritz since May 2015.

Jari Käyhkö studied paper technology in Helsinki University of Technology and graduated in 1994. After that he started in the Lappeenranta University of Technology as a researcher and completed his thesis "The influence of process condition on the deresination efficiency in mechanical pulp washing" in 2002. In 2003 Jari moved to Savonlinna working as a professor (pro tem) and started to build a new Pulp and Paper oriented research unit called FiberLaboratory. Now a days in the FiberLaboratory is working 20 people and Jari's main task is to lead research work related to the paper making. Studies in that field are mainly concentrated to the wet end of paper machine and the most important research area is the feeding of paper chemicals.

Kari Peltonen After graduation 1987 from the Technical University of Tampere Kari Peltonen joined Ahlstrom Oy Fiberflow division taking care of MC equipment development in different R&D projects. In 2001 Kari Peltonen started Andritz Oy Fiber Technologies Division as R&D manager of MC technology.

Yrjö Hiltunen, with expertise in environmental engineering, mechanical engineering and chemical engineering, graduated as a PhD from the University of Oulu, Finland. He also has a docentship in medical technology in the University of Oulu. Currently he is working as a research director in the University of Eastern Finland and in the FiberLaboratory of the Mikkeli University of Applied Sciences. His main research interests include data analysis, modeling, decision support and monitoring systems, and advanced measurement technology including nuclear magnetic resonance (NMR).