Automation of data processing obtained by IPI method

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Abstract

The paper describes an approach for automation of image processing obtained by IPI (Interferometric Particle Imaging), or also called ILIDS (Interferometric Laser Imaging for Droplet Size), method, which is used for measurement of spherical and transparent particle size. If the test section is relatively large and daylight can't be fully eliminated, signal noise is present in the measured data and conventional approaches used in the past can not be applied for automatic data evaluation. In this work is proposed an algorithm of interferogram detection based on cross-correlation, thresholding and Hough transform. The detection is then checked by region based convolutional neural network. The algorithm is programmed in Matlab and ImageJ (MIJ) and it is tested on data acquired during measurement of eliminator efficiency in a cooling tower.

Key-words: IPI, ILIDS, interference, cross-correlation, Hough transform, automation, experiment

1. Introduction and motivation

Particle sizing plays important role in many engineering applications, where dispersed two-phase flow can be found (sprays, bubble flow, cooling towers etc.) One of the frequently used methods for measurement of droplet size, spatial distribution and its velocity is noninvasive optical method called Interferometric Particle Imaging (IPI), also known as ILIDS (Interferometric Laser Imaging for Droplet Sizing) or MSI (Mie Scattering Imaging). The method captures the interference fringe (interferogram) of scattered laser sheet by a transparent spherical droplet. The interferogram is created by interference of two laser beams: reflected from a particle and refracted inside the particle. With high density of droplet in a test section, the fringes start to overlap. High-degree overlapping makes automatic particle's centre detection difficult and therefore it is not possible to evaluate diameter of all captured particles and consequently estimate the spatial distribution of droplet sizing in the test section. Basic methods for automatic droplet's centre detection are described in [1, 2]: thresholding, watershed and Hough transformation. These methods were used for image processing obtained from measurement in small scale models, where were good optical access and the camera was near the measurement plane. In measurements at larger models with high droplet density, the images were processed manually. Each interferogram had to be evaluated by a user, which led to time consuming data processing.

Even though the method is being developed since 1986 [3], development of algorithms for automatic evaluation is still current topic. The method based on edge detection and Hough transformation was used by Glover et al. [4]. They analysed the fringes automatically by a software suite that uses Gaussian blur, Canny edge detection and Hough transforms to locate individual droplets in the image. Quérel et al. [5] developed a global algorithm to calculate in real time the droplet diameter and spatial distribution from an ILIDS (IPI) interferogram. The algorithm performs a 1D Fourier transform to obtain a droplet size. Axis calibrations are then applied to get the spatial distribution as a function of the particle diameters. During the image analysis, noise reduction is also applied. Cross-correlation to locate particle's centre coordinate was used by Lacagnina [6]. At first, they converted the image in to the wavenumber domain by direct FFT. Then, the cross-correlation function between converted image and a reference image (white circle on a black background) was performed. Qieni et al. [7] proposed evaluation technique based on erosion match and FFT. The edge images of a droplet's interferogram and the particle mask image are detected respectively by erosion operating firstly and then subtracted with the respective original image. The centre coordinate of particles is then found using 2D correlation for the two edge images obtained. They performed tests on simulated data where all fringes had same brightness and contrast and the algorithm was able to identify all the simulated centres even with very high degree of fringe overlapping. But from test on real data could be seen, that presented algorithm did not evaluate fringes with low light intensity.

Also it is worth mentioning the work of Cuevas et al. [8], where authors presented general and robust algorithm for circle detection in noisy image using Learning Automata (LA) which is a probabilistic optimization method that explores an unknown random environment by progressively improving the performance via a reinforcement signal. The approach is based on encoding of three non-collinear points as a candidate circle over the edge image. A reinforcement signal indicates if the found candidate circles are actually present in the edge map.

In this paper, it is proposed algorithm based on work [1, 4, 6]. In first iteration of centre's coordinate evaluation, the image is transformed to wavenumber domain by FFT and cross-correlated with reference image. By the correlation value, the centre's coordinate are estimated. Based on the correlation value, the centre coordinate is evaluated. In second step, thresholding and Hough transformation is performed. With Hough transform it is possible to also detect the diameters of interferometric fringe patterns, because the diameters are different and the fringe diameter is dependant on the location in the image. Evaluated diameters are then mapped to centres detected in the first iteration.

Due to very large noise and fringe overlapping, the program in some case evaluate noise as a particle. To

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exclude misevaluated centres, region based convolutional neural network (R-CNN) is being employed.

The algorithm is programmed in Matlab, image postprocessing and thresholding is partly done in ImageJ running in MIJ environment in batch mode, controlled by Matlab through Java API. The program is described later in the text in detail.

2. Interferometric particle imaging (IPI)

A schematic of IPI is shown in fig. 1. When a transparent droplet is illuminated by a coherent laser radiation, the light is partially reflected from the surface and partially the light is transmitted through the particle, where is refracted (first-order refraction). This two rays are interfering with each other. If the image acquisition device (e.g. CCD camera, resp. CCD chip) is in focal plane, two glare points will appeared - one point for the reflected ray and the second one for the refracted. The interferogram (interferometric fringe pattern) is projected to defocused plane which lays between focal plane and and plane of imaging lens. The size (or diameter) of the interferogram depends only on the properties of optical apparatus, it isn't dependant on the size of light scattered particle.

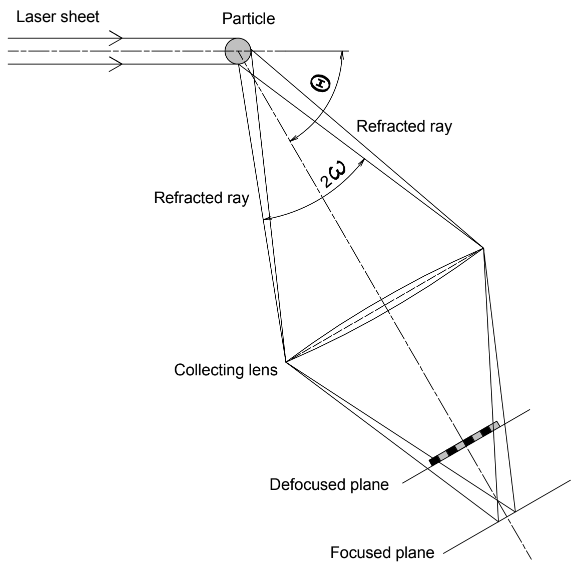

Fig. 1. *Typical configuration of IPI apparatus*

The droplet diameter d_{dr} can be calculated as [9]

$$d_{dr} = \frac{1}{cos\,(\Theta/2) + \frac{msin(\Theta/2)}{\sqrt{1+m^2-2mcos(\Theta/2)}}}\frac{\lambda}{\Delta\theta_m}, \qquad (1)$$

where $\Delta\theta_m$ is angular fringe spacing, m is refractive index of the droplet, λ is wavelength of light source and Θ is the observation (scattering) angle. More details about this equation can be found also in ref. [1]. The fringe spacing can be evaluated FFT technique using fitting of discrete Fourier power spectrum density [10], finding coefficients of quadratic cosinus function [1] or using Lorenz-Mie theory [1, 4].

2.1. Factors that influence the evaluation

Factors, that influence the evaluation of interferograms obtained by IPI method are in detail described in ref. [11].

The results from IPI method are sensitive to each light source, that is present in the experimental setup - day light, laser sheet reflection from rig construction, from overexposed particle etc. The signal noise affects evaluation of whole range of droplet's diameters. In the case of very small diameters, the evaluation of particle based on interferometric fringes is not possible, because the particle blends with the noisy background.

Other issue is created when in the test section are present droplets of various sizing (e.g. 15-400 μm). Intensity of the signal is dependant on the droplet diameter and large particles can be overexposed (the reflection/refraction intensity can even damage the CCD chip), but smallest particles has the same intensity as noise in the background and the background with the small particle blends together.

3. Determination of the centre of the interference fringe

This work is a continuation of [2] which was focused on creation of software for evaluation of interferograms. From the software is left the part dealing with evaluation droplet diameter based on interferometric pattern of the fringe. The software is updated by adding more robust automatic particle centre searcher capable identify droplets in noisy images. Example of such image is shown in fig. 3, where on the left can be seen original image from CCD camera and on the right is the result of postprocessing (adjustment of exposure, brightness, contrast and threshold was applied) to make visible all particles present in the image. The procedure (algorithm) how to identify as most particle as possible is described below and schematically is shown in fig. 2.

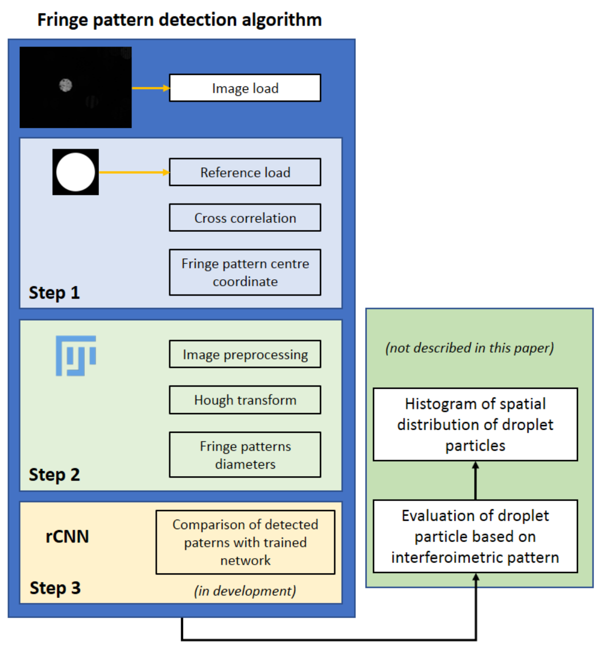

Fig. 2. *Diagram of the algorithm, steps in the blue box are described in this paper, procedures in green box were taken from ref. [2]*

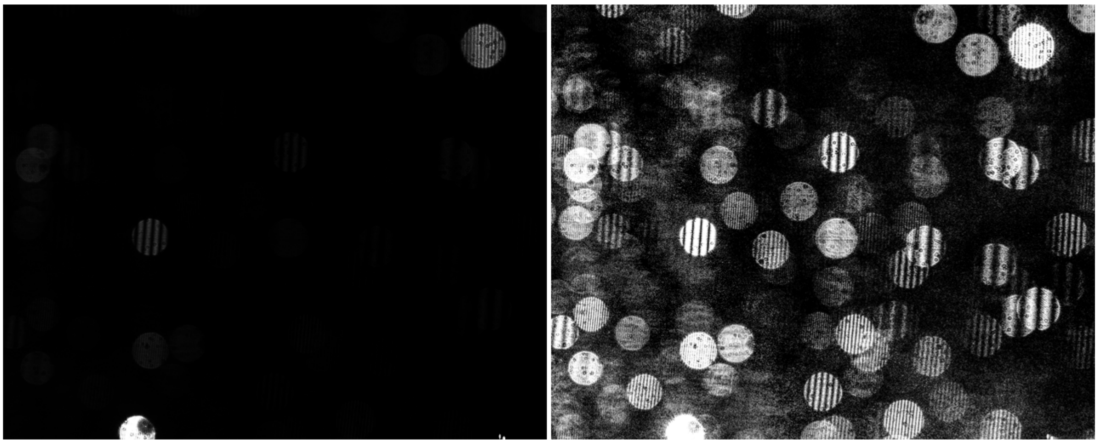

Fig. 3. ***Left****: Original image from CCD camera,* ***Right****: Postprocessed image with adjusted exposure, brightness and contrast to visualise all particles present in the image*

3.1. First step: Cross corelation

As first step, normalized 2D cross correlation of image with interferograms (example in fig. 3) with reference template (shown in fig. 2 in box Step 1) is applied. The image is transformed to frequency domain and it is correlated with the reference. Based on local sums, the correlation is normalized and the correlation coefficient is obtained (see fig. 4, where evaluated correlation coefficient is plotted). To find peaks of the cross correlation, at first the data are smoothed using 2D median filter to get rid of the noise in the correlation distribution and then, they are convolved with Gaussian. After the noise elimination, local maxima are evaluated using weighted centroids. Coordinates of the local maxima are centres of the interferometric fringe pattern.

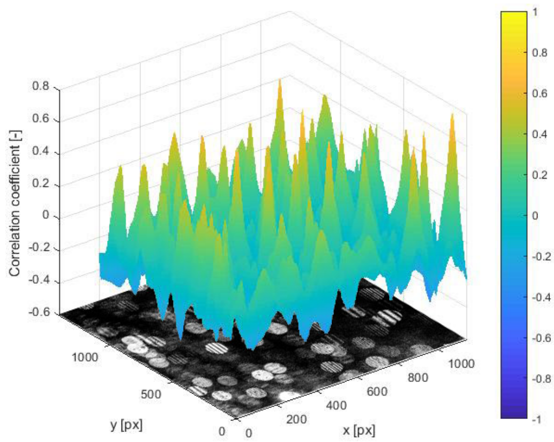

Fig. 4. *Distribution of correlation coefficient of original image and reference template in frequency domain*

3.2. Second step: Thresholding and Hough transformation

The CCD camera with the examining plane form an angle $\approx 60°$. When the interrogation area is relatively large, the optical way of the scattered ray is shorter from one area side than from the opposite horizontal side. Consequently, the diameters of the interferometric fringe patterns are increasing along horizontal axes. The diameter of the fringe and its spatial distribution along horizontal axis can be obtained from Hough transformation, but before, the image has to be preprocessed, because the Hough transformation would fail in noisy data.

For the data preprocessing, open source image processing program ImageJ is used with Java package MIJ for running ImageJ within Matlab in batch mode, thus all commands for image processing are run from Matlab Command window. ImageJ offers both local and global (histogram-derived) thresholding methods. ImageJ also include its own trainable segmentation tool called Weka [12] (Waikato Environment for Knowledge Analysis), which combines a collection of machine learning algorithms with a set of selected image features to produce pixel-based segmentations. As the future steps, Weka will be tested if it can increase the number of detected interferometric patterns.

The second steps of the algorithm consists following sub-steps. After the unprocessed image is load into Matlab, it is through MIJ open in ImageJ. In ImageJ are adjusted levels of the image followed by application of Minimum cross entropy threshold [13]. Then the edited image is returned back to Matlab workspace, where is applied Circular Hough transform to obtain diameters of the interferometric fringe patterns. Hough transform approach is used due to its relatively big robustness in the presence of noise, occlusion and varying illumination. Obtained spatial distribution of fringe's diameters is then mapped to centres evaluated in the first step by cross correlation.

3.3. Third step: Elimination of misevaluated patterns

The last step was added to procedure of evaluation fringe pattern for experimental purposes, because the author would like to test whether the deep learning approach can work with data where aren't many spatial features that could be used for training the network.

Convolutional Neural Networks (CNN) are able to identify spatial patterns in images. They are also resilient against small shifts and distortion. Using a weight sharing scheme, CNNs require a much smaller number of parameters to be tuned, therefore significantly simplifying the network training and computational complexity. [14]. Since lots of measurement with IPI method were performed and manually evaluated, very easily can be generated thousands of images of particles to train the network.

In the future, if the tests of CNN or any machine or deep learning approach are successful, this approach will the main tool used for image segmentation and detection of the particles.

The rCNN classifier is still under development. Used classifier's architecture is based on popular AlexNet neural network [15] and was trained on 10000 droplet images. The accuracy of this network set-up in the time of writing the paper is only 42%, which is low match. Future steps will be focused on the optimization of the network's architecture to achieve higher accuracy.

4. Results

The algorithm described above was on 40 images and the results of fringe pattern detection were compared with user evaluation. Approximately from 30 to 50 interferogramns were present at each image. Results are summarized in following table (table 1).

Average number of particle [1]	Correctly evaluated [%]	Misevaluated [%]
41.3	74.6 ± 6.2	6.7 ± 3.9

Table 1. *Summary of average results of comparison of manual evaluation with automatic approach presented in this paper, data averaged from 40 images*

From the table can be seen, that in some cases, the program could detect correctly more than 80% interferograms present in the image, which is very high percent. Even if the last step based on machine learning is not finished, the program is functional and in this stage can be used for fringe pattern evaluation and can save hours of user working time by automatic evaluation from 70% to 80% of interferograms obtained by IPI method.

5. Conclusion and future steps

In this paper was described an approach to automate processing of the detection of the interferometric fringe patterns, which is necessary for obtaining sizes of transparent particles. The fringes are captured with CCD camera by IPI method. The automation is based on cross-correlation of the original image with reference template in frequency domain and from the correlation are obtained coordinates of interferogram's centres. Since the camera forms an angle 60° with the illuminated plane, the diameter of interferometric fringe pattern is increasing along horizontal axes, so it is necessary to identify the spatial distribution of the diameters, which is then mapped to identified centres from cross-correlation. The diameters are obtained by Hough transform. With this procedure the program is able to detect 75% of interferograms. In the past, similar data were evaluated only manually, so 75% reduction of time is significant and it speeds considerably the process of data processing.

In the near future is planned to use algorithms of machine or deep learning, which could increase the percent of evaluated particles and decrease the number of misevaluated fringe patterns. The trend of using neural network can be seen for example in microbiology, where can be found many applications of machine and deep learning for image evaluation from past two years.

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