Automated Particle Size Measurement in Foundry Applications : A Study of Imaging Techniques

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Abstract

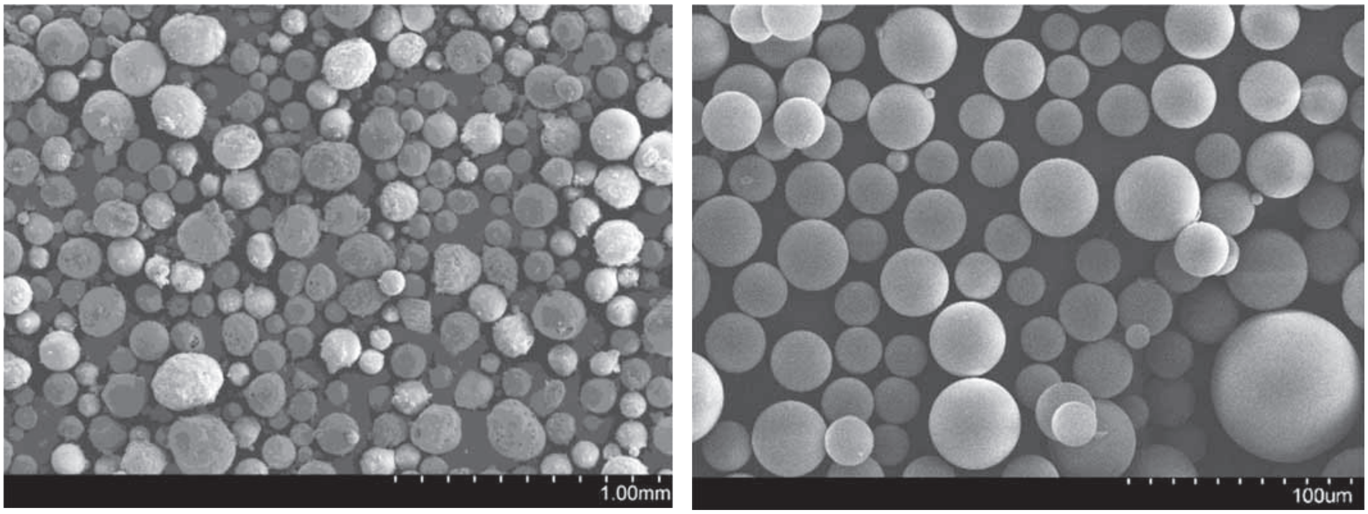
Particles are extensively utilised in the foundry industry for various applications. The size and distribution of sand particles are critical for determining their packing fraction in sand moulds. Additionally, particles are incorporated into metals to produce metal matrix composites, where particle size influences the particle-matrix interfacial area. Traditional sieve shakers measure powder particle size but provide only a discrete distribution based on the sieve sizes used. For a comprehensive and continuous measurement of particle size distribution, imaging methods are employed to analyse particle images, allowing for the capture and measurement of individual particle sizes. This study focuses on applying image processing techniques to enhance the quality of particle micrographs and develop a reliable particle size measurement method.

Introduction

The foundry industry is modernising by adopting advanced tools and technologies to enhance casting quality. Ongoing efforts aim to increase automation and computerisation. Modelling and simulation techniques have proven beneficial in developing process parameters, designing efficient moulds, and estimating the quality of cast parts. Furthermore, machine learning is being explored for advancements in various domains, including mould design and process development[1]. Imaging techniques are integral to the casting industry, with optical and electron microscopes, optical and thermal cameras, and CT scanners providing essential information about raw materials, processes, and finished castings. This work leverages image analysis methods for the assessment of powder particle sizes.

Integrating sensors and imaging technologies enables scientific analysis of various types of powder particles. Powders are widely utilised in the foundry for adding ingredients or creating porous beds for infiltration. Particulate composites are also prevalent[2, 3]. Figure 1 illustrates two common particle types: (a) fly ash cenospheres sourced from thermal power plant ash and (b) high-quality engineered glass hollow particles. Fly ash particles are irregularly shaped with structural defects, while glass particles are produced through controlled processes and are predominantly spherical and defect-free. Both types of particles, with diameters ranging from 10 to 250 μm, are extensively used in cast composite materials[4, 5] . Numerous studies highlight the impact of particle size on the properties of composite materials.

The packing factor of powder particles is influenced by multiple parameters, the most critical of which is particle size distribution[6]. Accurately measuring particle size and distribution is essential for developing processing parameters during casting. Various methods for measuring powder particle size are available, including imaging and diffraction-based techniques. Imaging methods have increasingly incorporated machine learning approaches[7]. For these machine learning techniques to



(a) (b)

Fig 1: (a) Fly ash particles obtained from thermal power plants and (b) engineered hollow glass particles

be effective, the images must undergo processing, and models must be trained. Established image processing methods exist that do not require extensive training while still effectively measuring powder particles.

Image analysis approaches for particle size measurement

Two primary approaches are employed to measure the diameter of powders in images. The first involves measuring labelled regions achieved through segmentation, which allows for individual particle measurements but requires resolving the complex task of image segmentation. The second approach applies filters to the image, where the response varies according to the spatial structures present, yielding statistical measurements on a per-area basis instead of per particle. The following discussion demonstrates the application of established techniques for each approach using a sample image of glass particles to measure their diameter and size distribution. These methodologies are applicable to metal particles or any other material type.

Watershed segmentation

Watershed segmentation is a widely utilised technique in image processing for effective partitioning of objects within an image[8]. This method is particularly advantageous when dealing with images containing touching or overlapping objects. The analogy of "watershed" refers to the operational principles akin to natural water distribution into distinct basins within a topographical landscape. By transforming the input image so that pixel values represent the likelihood of boundary presence, the Watershed Algorithm floods the image from local minima to create boundaries where adjacent floods converge.

The implementation of the Watershed Algorithm for microscopic image segmentation follows the methodology presented in Ref [9], which aims to reduce over-segmentation when analysing Ti-6Al-4V microstructures. A Hitachi S3400N scanning electron microscope captures the raw images of glass particles (shown in Fig 2(a)), which are processed using the HED network discussed previously. These particles are commonly used in metal and polymer matrix composites[10-12]. The

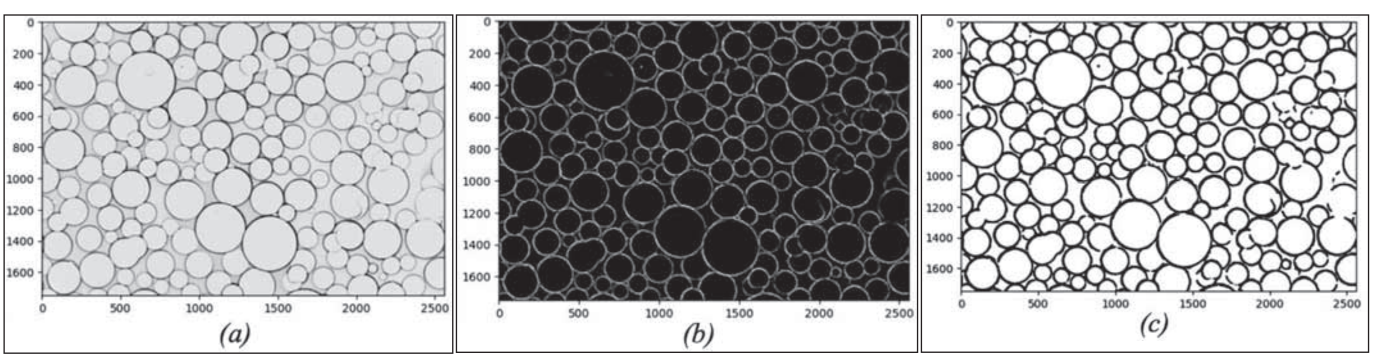


Fig 2: Illustration of pre-processing of raw image for effective watershed segmentation: (a) raw image, (b) output image after forward passing the raw image into the HED network, (c) denoised image. The numbers on x and y axes corresponds pixels

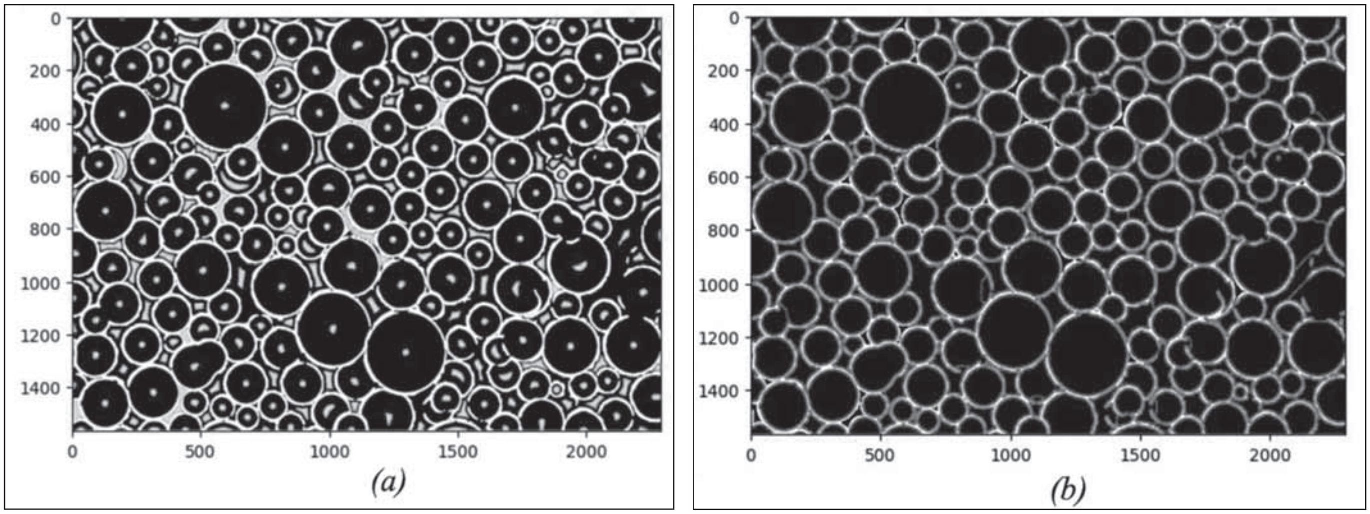


Fig 3: Illustration of images in watershed algorithm: (a) marker image, (b) watershed segmented image. The numbers on x and y axes corresponds pixels

outcomes of the HED method are displayed in Fig 2(b). Morphological opening [13] is employed to eliminate noise from the glass particles, utilising a rectangular-shaped structuring element of dimensions (1,3). To further minimise noise, a median filter with a square kernel size of (7, 7) is applied. The algorithm subsequently dilates the denoised image using a kernel size of (5, 5), aiding in the filling of broken boundaries of the glass particles. Final binary thresholding is performed with a threshold value of 100, resulting in the inverted image shown in Fig 2(c).

The Watershed implementation from Ref [9] employs the image's gradient magnitude as the topographic function, computing a set of markers based on the distance transform while suppressing its least significant local maxima. Here, this approach is modified to utilise the HED instead of the distance transform, thereby improving segmentation accuracy. Each particle is identified based on detected edges with a single marker, as shown in Fig 3(a), while changes in grayscale intensity delineate boundaries between these markers, illustrated in Fig 3(b). This segmentation enables precise measurement of each particle.

Feature Length Orientation Space (FLOS)

Measurements of spatial structures in images can be obtained without segmentation using mathematical morphology techniques[14]. The impact of a morphological operator on an image depends on the size and shape of a predefined structuring element related to the image's spatial structures. Granulometric methods repeatedly apply these techniques with incrementally larger structuring elements, recording variations in output. One successful method in microstructural analysis is the Feature Length Orientation Space (FLOS)[14] . This technique fits linear elements of varying lengths and orientations to the image and records the response in the FLOS, allowing computation of various properties of the spatial structures, such as width, length, and globularity. The FLOS technique can be applied to a

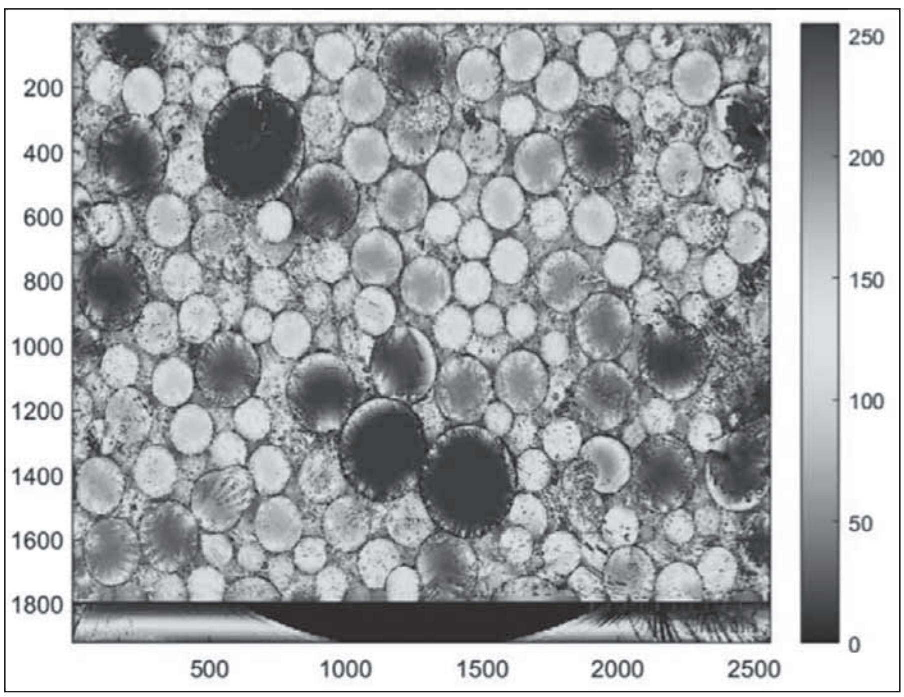


Fig 4: Illustration of FLOS technique on powder particles. The numbers on x and y axes corresponds pixels

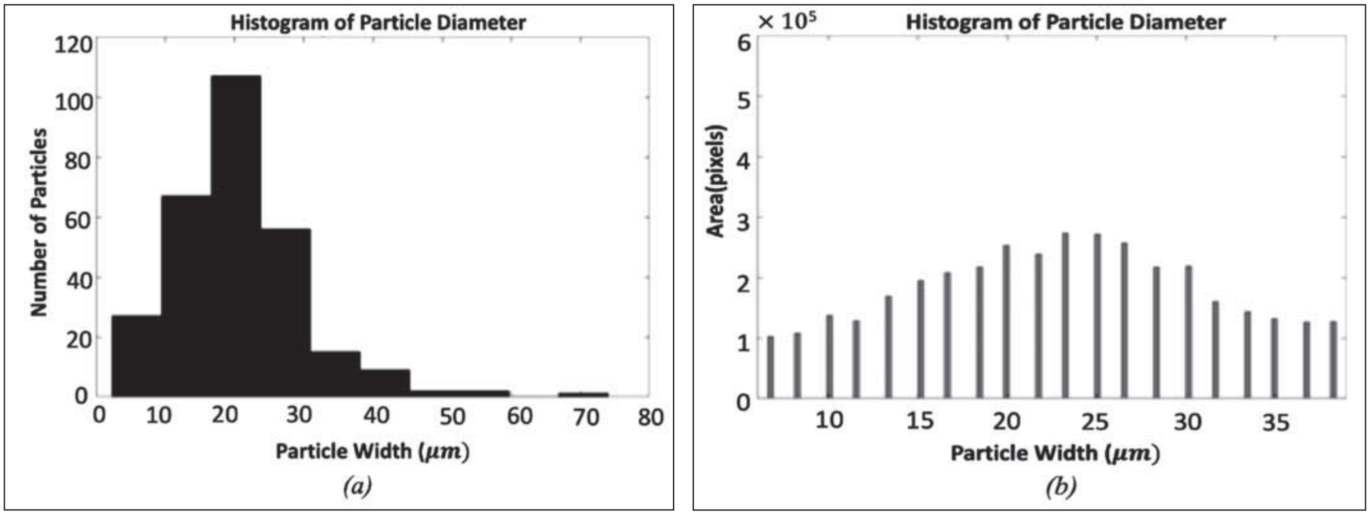


Fig 5: Histogram plots using watershed and FLOS technique. (a) watershed histogram, (b) FLOS histogram

greyscale image formatted so that the foreground is bright, with width measurements approximating grain size due to the spherical nature of the objects. The FLOS technique reports spatial structure sizes on a per-pixel basis, assigning each pixel a value corresponding to the estimated property of the object it belongs to. This information can be visualised using colour maps, as shown in Fig 4, where larger particles are indicated in deep shade, highlighting them as the largest structures in the image.

Results for particle size measurement

The pixel-to-micron ratio obtained from the scale in the raw image is 6; thus, 600 pixels correspond to 100 microns, as indicated by the scale bar. The results from both the watershed and FLOS techniques are presented in histogram format in Fig 5. The watershed method yielded a mean grain size of 20.68 μm, while the FLOS method provided a mean width of 24.24 μm. The comparability of results from both approaches is encouraging. Each method measures a range of additional properties beyond grain size, enabling the filtration of measurements according to the expected properties of the microstructure (thereby avoiding erroneous measurements of improbable size and shape). However, specific data refinements were not employed to prevent overfitting, further reinforcing the reliability of the relative agreement. Both methods also yield visualisations that confirm the reliability of the results, with segmentation shown in Fig 3 indicating boundaries in correct locations and Fig 4 displaying a colour map accurately depicting the largest particles' locations.

The measured mean particle sizes from the two methods are: Watershed = 20.68 μm and FLOS = 24.24 μm. These size measurements can be refined by further tuning the processes based on a larger set of images. The examples presented in this study demonstrate the feasibility of conducting analyses using image processing methods, which can be implemented in computer programmes for automated and rapid analysis of particle samples.

Table-1 shows the differences between Watershed Segmentation and Feature Length Orientation Space (FLOS) techniques.

Summary of differences

Segmentation vs measurement: Watershed segmentation isolates individual objects, while FLOS provides statistical measurements across the image.

Approach: Watershed relies on topographic analogy for boundary detection; FLOS uses morphological techniques to analyse shapes.

Output Type: Watershed yields distinct segmented regions, whereas FLOS produces continuous data reflecting the properties of the structures within the image.

Both methods can complement each other in image analysis, with watershed segmentation offering precise object delineation and FLOS providing broader statistical insights.

Conclusions

In conclusion, this paper presents innovative imaging methods for particle size measurement that offer significant advancements over traditional sieve analysis used in the foundry industry. By employing techniques such as watershed segmentation and Feature Length Orientation Space (FLOS), the study enables continuous and automated analysis of particle size distribution,

Table-1: Differences between Watershed Segmentation and Feature Length Orientation Space (FLOS) techniques

		Watershed Segmentation	Feature Length Orientation Space (FLOS)
1	Purpose	Primarily used for segmenting objects within an image, particularly when they are touching or overlapping.	Focuses on analysing 3-D structures without requiring full segmentation, providing statistical measures of features in the image.
2	Methodology	It treats the image like a topographical surface where pixel intensities represent elevation. It identifies local minima (like basins) and simulates flooding from these points to create boundaries where adjacent floods meet. The result is a segmented image where each object (eg, particles) is isolated for individual measurement.	It applies morphological operations using structuring elements of varying sizes and orientations to extract features from the image. The technique fits linear elements to the spatial structures and records responses in a feature space, which captures properties such as width, length, and orientation.
3	Output	Produces labelled regions corresponding to distinct objects in the image, allowing for precise measurements of individual particles.	Produces statistical information about the particles, such as their size and shape, without creating distinct labelled segments. It generates a per-pixel response that reflects the characteristics of the structures.

enhancing efficiency and accuracy. The successful application of these methods to glass particles, along with their potential applicability to various materials, demonstrates their versatility. The comparative analysis of both approaches yields reliable results, reinforcing the effectiveness of imaging techniques in characterising powder particles. Furthermore, these advancements lay the groundwork for future integration with machine learning, promising even greater improvements in the precision and automation of particle size measurement processes. Overall, this work highlights a crucial step towards modernising practices in the foundry industry, facilitating better quality control and process optimisation.

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