

Automated Detection of Primary Particles from Transmission Electron Microscope (TEM) Images of Soot Aggregates in Diesel Engine Environments

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ABSTRACT

The major challenge of the post-processing of soot aggregates in transmission electron microscope (TEM) images is the detection of soot primary particles that have no clear boundaries, vary in size within the fractal aggregates, and often overlap with each other. In this study, we propose an automated detection code for primary particles implementing the Canny Edge Detection (CED) and Circular Hough Transform (CHT) on pre-processed TEM images for particle edge enhancement using unsharp filtering as well as image inversion and self-subtraction. The particle detection code is tested for soot TEM images obtained at various ambient and injection conditions, and from five different combustion facilities including three constant-volume combustion chambers and two diesel engines. Through a comparison between automatically detected and manually selected primary particles from extensive datasets, five key image-processing parameters of the self-subtraction level, negative Laplacian shape parameter, maximum and minimum diameter of primary particles, and CHT sensitivity are optimised. From the analysis of the size distribution and mean diameter of primary particles, it is found that the automatic method is much more dependent upon the minimum primary particle diameter and CHT sensitivity than the other three parameters. With the optimised set values, the new particle detection code shows a good agreement with the results from the manual method.

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INTRODUCTION

Diesel soot particles within a diesel flame [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15] or in the exhaust stream [16, 17, 18, 19, 20] show aggregate structures composed of various numbers of spherical primary particles. The soot aggregates vary not only in size but also in shape ranging from long-stretched to highly agglomerated structures. The number of primary particles in each aggregate also varies from the aggregates comprised of tens of primary particles to double-primary (dimer) aggregates or even single-primary (monomer) particles. Many studies report a correlation between the soot structures and their toxicity [21, 22, 23, 24, 25], particularly noting high reactivity of ultrafine particles to cause the potential

damage of a respiratory system [26,27]. Therefore, the need is clear for a correct measurement of the size and shape of soot aggregates as well as primary particles.

The sampling of soot aggregates on a carbon-coated mesh grid and subsequent transmission electron microscope (TEM) imaging is the most popular technique to clarify soot size and structures [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]. The indexing and size measurement of soot aggregates is straightforward since the binary TEM image using a threshold-based boundary detection algorithm can provide the radius of gyration of each aggregate [4]. However, the detection of primary particles within diesel soot aggregates poses a significant challenge due to the blurred particle boundaries and the particles overlapping [8,9].

A correct measurement of the primary particle diameter (d_p) is critical for the analysis of aggregate morphology and soot optical properties such as fractal dimension (D_f) and dimensionless extinction coefficient (k_e), respectively. For instance, the characteristic fractal dimension may be obtained using the following power law function [6]:

$$N = k_f \left(\frac{R_g}{\bar{d}_p} \right)^{D_f} \quad (1)$$

where N is the number of primary particles within a soot aggregate, k_f is the fractal prefactor, R_g is individual soot aggregate size, and $\bar{d}_p$ is the mean diameter of primary particles of each aggregate [28]. The D_f and k_f can be obtained by reading the slope and the intercept of the least-square straight line of a plot $\ln(N)$ over $\ln(R_g/\bar{d}_p)$. In this equation, higher D_f of a certain soot aggregate means more compacted shapes while a lower fractal dimension indicates more stretched aggregates. The N in Eq. (1) can also be obtained using R_g and $\bar{d}_p$ [29]:

$$N = k_a \left(\frac{A_a}{A_p} \right)^\alpha = k_a \left(4 \frac{R_g^2}{\bar{d}_p^2} \right)^\alpha \quad (2)$$

where A_a is the projection area of a soot aggregate and A_p is the mean projection area of primary particles of the aggregate. Previous studies suggest that the empirical constant k_a varies from 1 to 1.81 while the primary particle overlap factor α is in the range of 1.08~1.19 [29, 30, 31, 32, 33, 34]. In Eqs. (1) and (2), it is clear that the measurements for d_p is very important to obtain the number of primary particles of each aggregate and the fractal dimension.

Another instance in which d_p plays a key role is the estimation of the dimensionless extinction coefficient. Soot volume fraction (f_v) is determined from the dimensional extinction coefficient data using the following relationships [35]:

$$f_v = \frac{K\lambda}{k_e} \text{ and } k_e = (1 + \rho_{sa})6\pi E(m) \quad (3)$$

where K is the extinction coefficient, λ is the laser wavelength, k_e is the dimensionless optical extinction coefficient, ρ_{sa} is the scattering-to-absorption ratio, m is the refractive and $E(m)$ is a function of the refractive index of soot:

$$E(m) = -Im \left(\frac{m^2-1}{m^2+2} \right) \quad (4)$$

In Eq. (3), the ρ_{sa} can be obtained using the Rayleigh-Debye-Gans scattering absorption theory for polydisperse fractal aggregates (RDG-PFA) [36, 37, 38]:

$$\rho_{sa} = \frac{N^2}{N} \omega_p \left\{ \left(1 + \frac{4}{3D_f} \left(\frac{2\pi}{\lambda} \right)^2 R_g^2 \right) \right\}^{-D_f/2} \quad (5)$$

and

$$\omega_p = \frac{2}{3} \left(\frac{2\pi}{\lambda} \right)^3 \left(\frac{d_p}{2} \right)^3 \frac{F(m)}{E(m)} \quad (6)$$

In Eq. (5), ω_p is the albedo of a primary particle and $F(m)$ is a function of the refractive index of soot:

$$F(m) = \left| \frac{m^2-1}{m^2+2} \right|^2 \quad (7)$$

Equations (5) and (6) suggest that the measured d_p together with R_g and D_f from Eq. (1) can provide the dimensionless extinction coefficient. Therefore, the motivation is clear for the accurate measurement of d_p .

Despite its importance, the d_p measurement is heavily dependent upon a manual selection of primary particles from TEM images [4, 5, 6, 8, 9, 13]. Manual detection methods require substantial time and effort to obtain large numbers of primary particles for statistically meaningful results. For biological macromolecules applications, automated particle detection from electron micrographs has been attempted based on component labelling and feature computation [39] or textual methods [40]; however, the level of false positives remains high and there is no guarantee that these methods would be directly applicable for soot particles.

Recently, Grishin et al. [41] developed an automated detection method for soot primaries which is based on the Circular Hough Transform (CHT) [42]. The CHT algorithm functions by fitting circles of various sizes onto pixels that are identified as "candidate pixels" [43]. Prior to the CHT, the Otsu threshold algorithm, rolling-ball transform (smoothing), and an edge-following algorithm (Papert's turtle approach) are used for noise reduction, boundary cleaning, and identification of the edges of the soot aggregates, respectively, as their method uses the boundary pixels as the candidate pixels. The results are a series of curve fragments, which can be fed into the CHT for the primary particle detection. Due to unexpectedly high curvature fragments, the regularisation is required but the final product shows a good agreement with manually selected primary particles.

This study presents the improvement of the CHT-based automatic detection of soot primary particles in two aspects. One is the use of Canny Edge Detection (CED) [44] for the processing of not only the aggregate edge pixels but also inner pixels because some primary particles are surrounded by other primary particles within each aggregate. The CED was promising because a similar method was successfully applied to the detection and sizing of subsurface spherical particles shown in noisy and low contrast TEM images [45]. The other is the pre-processing of TEM images using image inversion and self-subtraction as well as unsharp filtering (negative Laplacian transform), which is expected to enhance the particle boundaries while suppressing noise signals. How each of image-processing parameters affects the automated primary particle detection is also discussed for soot particles sampled directly from diesel flames in both a constant-volume combustion chamber and a diesel engine. The results are compared to our previous data obtained using a manual selection method. The full Matlab code used in this study and its application to three different sets of soot TEM images from three other diesel combustion facilities are also presented.

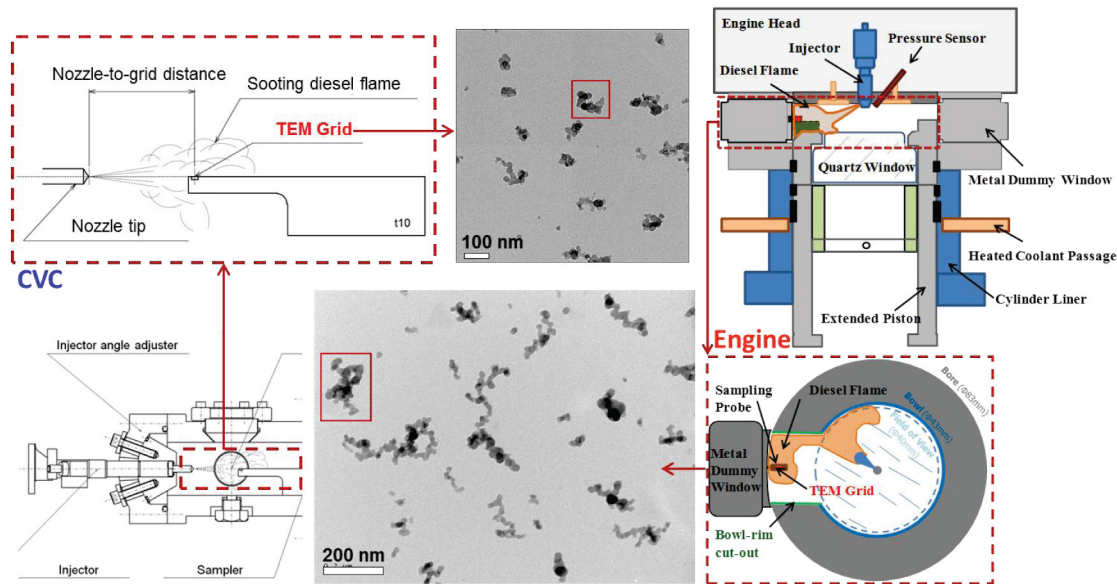


Figure 1. The CVC schematic (bottom-left), soot sampling method (top-left), and a TEM image (top-middle) of Meiji University and the engine schematic (top-right), soot sampling method (bottom-right), and a TEM image (bottom-middle) of UNSW.

SOOT SAMPLING EXPERIMENTS

The sampling of soot particles was conducted in five different facilities simulating diesel engine conditions, of which three are optically-accessible, pre-burn-type constant-volume combustion chambers (CVC) available at Meiji University [3,4,6, 7, 8,11,12,14,15], Sandia National Laboratories [2,4,35,46], and IFPEN [47, 48, 49], and the other two are diesel engines housed in the University of New South Wales (UNSW) [9,10,13] and Lund University [50]. In this study, soot samples from the Meiji CVC and the UNSW diesel engine were used for the development of the new particle detection code and its performance evaluation for various image-processing parameters. The two facilities were selected because extensive datasets of the soot primary particles are available from the manual selection methods, which can be compared to the new data from the automatic method. The ambient gas and injection conditions of these two facilities were also very close. Soot samples from the other three facilities were used to demonstrate the efficacy of the new code and selected image-processing parameters, and to provide example cases for various soot samples. Details about the used facilities and operating procedures for soot sampling experiments are found in our previous studies [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 46, 47, 48, 49, 50, 51] and thus only a brief summary is provided in this section.

MEIJI UNIVERSITY CONSTANT-VOLUME COMBUSTION CHAMBER

Figure 1 shows the schematic of the Meiji CVC (bottom-left), soot particles sampling (top-left), and a TEM image of sampled soot particles (top-middle). The ambient gas and fuel injection conditions are listed in Table 1. The chamber was operated so that fixed ambient gas conditions of 2.5 MPa, 940 K, and 21% O₂ concentration are created at the time of fuel injection and throughout the diesel combustion event using the spark ignition of ultra-lean mixture of acetylene, oxygen and nitrogen. A conventional diesel fuel (JIS#2)

was injected via an axially-drilled, 140-μm hole of a common-rail injector at fixed rail pressure of 80 MPa for the injection duration of 2.5 ms, which corresponds to 10.3 mg of fuel mass per injection.

The soot particles were sampled at 70 mm from the nozzle, which was about 65 mm downstream of the flame base at 5 mm from the nozzle and where the highest amount of soot is measured [3,4,7,11,15]. The thermophoretic force (i.e. positive thermal diffusion) between high-temperature soot particles within the flame and a cold (373 K) carbon-coated copper mesh was used for the sampling, which is believed to quench the soot reactions instantly [30]. The sampling probe placed in parallel to the sooting diesel flame (see Fig. 1) has a small 3-mm-wide and 1.5-mm-deep opening at the tip, which provides a passage for the soot-laden gas flow while protecting the 3-mm copper grid from excess heat, consistent with Refs. [2,4].

A transmission electron microscope (JEOL JEM-2100F) readily available at Meiji University was used to take high-magnification soot images. The specified point resolution of the microscope is 0.19 nm and the electron acceleration voltage is 200 keV. All images were digitally recorded using a CCD camera (Gatan UltraScan 1000) with an image resolution of 2048 by 2048. An example image is shown at the top-middle of Fig. 1, which shows various soot aggregate structures. A selected aggregate (illustrated by a red square) will be used for the discussion of the automated detection of soot primary particles in the following sections.

Sandia National Laboratories and IFPEN Constant-Volume Combustion Chambers

The other two CVCs at Sandia [2,4,35,46] and IFPEN [47, 48, 49] operate in a very similar manner in terms of the pre-burn of ultra-lean mixture to create high-temperature and high-pressure ambient gas conditions of diesel engines as well as the use of an axially drilled single-hole nozzle in a common-rail injector. As summarised in Table

2 and 3, however, the Sandia CVC was run at higher ambient gas pressure condition (6.7 MPa), lower ambient O₂ concentration (15%), and higher injection pressure (150 MPa) than those of the Meiji CVC. In comparison, the IFPEN CVC had the same 21% O₂ concentration as of the Meiji CVC but higher ambient gas pressure of 6 MPa and higher injection pressure of 150 MPa, similar to the Sandia CVC (i.e. O₂ concentration variants of the ECN Spray A target conditions [46]). The fuel used for the IFPEN (n-dodecane) was different to the Meiji and the Sandia experiments (conventional diesel fuel). Variations in ambient gas and fuel injection condition are well known to affect the soot particles [4,13,15,20]. Therefore, the soot particles sampled from these CVCs provide a good opportunity to test the new automated detection method for a wide variety of soot sizes and structures.

Table 1. Meiji University CVC operating conditions

Ambient gas conditions	
Density	9.5 kg/m ³
Temperature	940 K
Pressure	2.5 MPa
O ₂	21%
Injection conditions	
Type	Common-rail
Nozzle	Single-hole, mini-sac
Nozzle diameter	140 µm (nominal)
Injection pressure	80 MPa
Injection duration	2.5 ms
Fuel	JIS#2
Mass per injection	10.3 mg
Sampling location from nozzle	70 mm (peak soot)

Table 2. Sandia CVC operating conditions

Ambient gas conditions	
Density	22.8 kg/m ³
Temperature	1000 K
Pressure	6.7 MPa
O ₂	15%
Injector conditions	
Type	Bosch common-rail second-generation injector
Nozzle	Single-hole, KS1.5/0.86, mini-sac
Nozzle diameter	90 µm (nominal)
Injection pressure	150 MPa
Injection duration	7 ms
Fuel	No. 2 Diesel
Sampling location from nozzle	50 mm (peak soot)

Table 3. IFPEN CVC operating conditions (O₂ Variants of ECN Spray A target conditions [46])

Ambient gas conditions	
Density	22.8 kg/m ³
Temperature	900 K
Pressure	6.0 MPa
O ₂	21%
Injector conditions	
Type	Bosch common-rail second-generation injector
Nozzle	Single-hole, KS1.5/0.86, mini-sac
Nozzle diameter	90 µm (nominal)
Injection pressure	150 MPa
Injection duration	6 ms
Fuel	N-dodecane
Sampling location from nozzle	45 mm (peak soot)

The soot sampling experiments were conducted using a similar method as in the Meiji CVC (details are found in our previous work [2,49]). Regarding TEM imaging, the soot samples (TEM grids) from the IFPEN CVC were sent to Meiji University for processing and thus the same method and set values of the Meiji TEM were used. However, the Sandia samples were processed at an in-house facility [2,4]. Obviously, different microscopes used by different operators can lead to variations in the resulting TEM images. To address this issue, the new code implements a background correction step prior to the edge detection and primary particle recognition as will be discussed later in the Algorithms section.

UNSW Optical Diesel Engine

Figure 1(right) shows the schematic of the UNSW single-cylinder optical diesel engine used for in-flame soot sampling experiments via thermophoresis. Specifications of the engine and its operating conditions are listed in Table 4. The engine has a displacement volume of 498 cc with a small 83-mm bore and 92-mm stroke, typical of a light-duty diesel. To create thermally stable engine conditions, the wall temperature was held constant at 363 K by circulating heated water to the engine head, cylinder liner and engine block. All experiments were conducted at fixed engine speed of 1200 revolutions per minute (rpm) controlled by an electric motor.

The used fuel was a conventional ultra-low-sulphur diesel with cetane number of 51. The fuel injection system was composed of a Bosch second-generation common-rail and a 134-µm single-hole injector. At fixed rail pressure of 70 MPa, the injection occurred for 2.34 ms, which corresponds to 9 mg of fuel mass per injection. It should be noted that these injection conditions are very similar to the Meiji CVC conditions (see Table 1). The injection timing was fixed at -7 crank angle degrees after top dead centre (°CA aTDC) and a 10-skip-firing strategy (injection every 10th cycle) was used to minimise cyclic dispersion caused by residual gas from previous firing cycles.

For the soot sampling, a similar method to the Meiji soot sampling was used involving a carbon-coated copper grid with 400 meshes and a restrictive passage (1-mm hole) at the sampling probe tip. As shown in Fig. 1(right), however, the sampling probe was not parallel to the sooting diesel flame but was placed within a 30-mm-wide bowl-rim cut-out region. This bowl-rim cut-out was required to avoid a potential crash between the stationary sampling probe and the fast-moving piston [9]. The TEM grid was located about 62 mm from the nozzle along the jet travelling trajectory. A transmission electron microscope (JEOL 1400) with a point resolution of 0.38 nm and an accelerating voltage of 120 kV was used to obtain high-magnification soot images, which was available at UNSW. A CCD camera with a resolution of 11 mega pixels was used to digitise soot particle images. An example image is shown at the bottom-middle of Fig. 1. Similar to the Meiji CVC image, a selected aggregate for the discussion of the automated detection method is illustrated by a red rectangle.

Table 4. UNSW single-cylinder optical light-duty diesel engine specifications and operating conditions

Number of cylinders	1
Displacement volume per cylinder	498 cm ³
Bore / Stroke	83 mm / 92 mm
Compression ratio	15.2
Swirl ratio	1.4
Coolant temperature	363 K
Intake air temperature	303 K
Intake O ₂	21%
Engine speed	1200 rpm
Fuel	Ultra-low-sulphur diesel
Cetane number	51
Injection system	Bosch common-rail second-generation injector
Nozzle type	Single-hole, K1.5/0.86
Hole diameter	134 µm (nominal)
Injection pressure	70 MPa
Injection duration	2.34 ms (actual)
Mass per injection	9 mg
Injection timing	-7°CA aTDC

Table 5. Lund University six-cylinder heavy-duty diesel engine specifications and operating conditions

Number of cylinders	6
Displacement volume per cylinder	2130 cm ³
Bore / Stroke	131 mm / 158 mm
Compression ratio	16
Exhaust gas recirculation	43.3%
Intake O ₂	10.4%
Engine speed	1200 rpm
Fuel	Ultra-low-sulphur diesel (MK1)
Cetane number	51
Injection system	Delphi E3 Unit Injector
Nozzle type	6 holes
Hole diameter	219 µm (nominal)
Injection pressure	200 MPa maximum
Equivalence ratio	0.645
IMEP	1 MPa
Combustion phasing (CA50)	3°CA aTDC

Lund University Diesel Engine

The Lund University diesel engine [50] is an in-line six-cylinder 12.78-litre engine with a large bore and stroke of 131 and 158 mm, respectively for heavy-duty applications. The engine specifications and operating conditions are listed in Table 5. The multi-cylinder engine was used for the soot particles sampling in the exhaust, which is complementary with the in-flame sampling conducted in the UNSW's light-duty diesel engine. The engine was run at 1200 rpm with 43.3% of a recirculation ratio of the exhaust gas resulting in 10.4% oxygen concentration in the intake air. Similar to the UNSW engine, a conventional ultra-low-sulphur diesel with cetane number of 51 was injected using a six-hole unit injector at maximum injection pressure of 200 MPa. The fuel injection was adjusted for the estimated equivalence ratio of 0.645, corresponding to 1 MPa indicated mean effective pressure (IMEP) conditions at fixed CA50 (crank angle location for 50% heat release) of 3°CA aTDC.

The Lund diesel engine was used for exhaust soot sampling, similar to our previous work [51]. The exhaust gas was diluted using a two-stage ejector dilution system (Dekati) performing 1:8 dilution with 431-K filtered air and additional 1:15 dilution with air at room temperature. Between the two dilution processes, the gas was heated to 573 K for about 2 seconds to remove low volatility organics from the particles. This setup corresponds to the European PMP sampling standard, which is developed to avoid nucleation of volatile nanoparticles and condensation of low volatility organics on the soot aggregates. The soot aggregates in the diluted exhaust gas were sampled using an electrostatic precipitator (Nanometer Aerosol Sampler Model 3089, TSI) at a 9.6-kV voltage and 1-lpm flow rate conditions. The sampled soot aggregates were imaged in the Meiji transmission electron microscope.

AUTOMATED DETECTION METHOD

Algorithms

The new method for automated particle detection involves four steps including image inversion and self-subtraction, unsharp masking based on the negative Laplacian transform [52,54], Canny Edge Detection (CED) [44], and Circular Hough Transform (CHT) [42,43]. The full code written on Matlab (version 2012a or higher) with an image processing toolbox is provided in the Appendix section. The overall procedure for the image processing is shown in Fig. 2. A digitised TEM image contains about 20~30 soot aggregates. A selected soot aggregate (see Fig. 1) from the UNSW diesel engine data is used as an example in this figure.

The background of TEM images varies sample by sample and image by image due to the differences in the carbon film and the magnification/intensity setting of TEM imaging. This was corrected by applying the combination of image inversion and self-subtraction. In TEM images, the soot particle regions show lower image counts than the carbon film area (e.g. the top-left of Fig. 2). The image inversion through the subtraction of the original image count from the maximum image count of the TEM image results in higher image counts in the soot particle region for easier threshold determination in the following steps. Then, the original TEM image is subtracted from the inverted image. This self-subtraction procedure effectively

increases the image contrast because brighter soot particle regions in the inverted TEM image undergo less image count reduction compared to darker carbon film regions. Some pixels with negative image counts as a result of this self-subtraction are set to zero value, leading to a black background, as shown in Fig. 2 (top-middle).

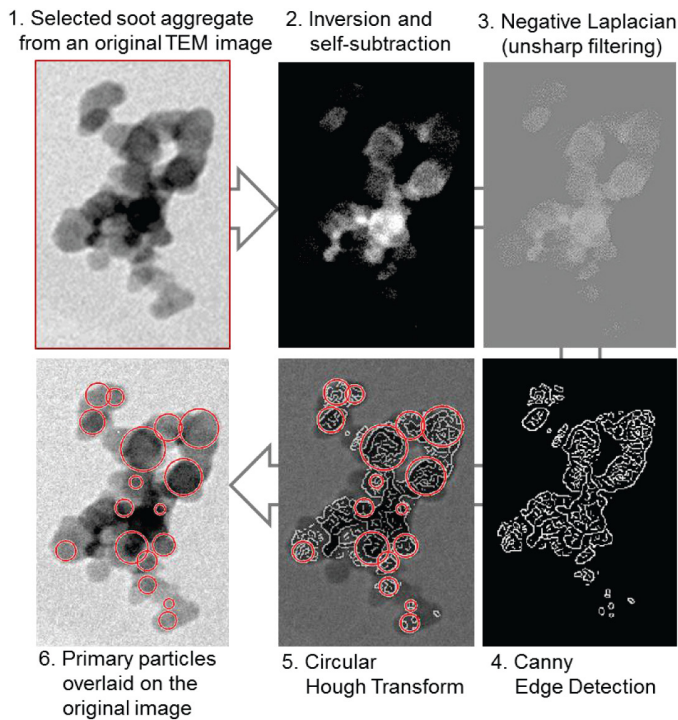


Figure 2. The image processing steps for the automated detection of primary particles. The soot aggregate used as an example is the same aggregate from the UNSW sample in Fig. 1.

The next step is a 3-by-3 unsharp filtering to enhance the edges of soot primary particles. The unsharp filter is from the negative of the Laplacian filter with a selected control parameter for the Laplacian shape [52,54]. The resulting image is shown in Fig. 2(top-right).

The sharpened image works as an input to the Canny Edge Detection (CED) utilising a multi-stage algorithm to detect a wide range of edges [44,45]. The CED consists of five steps including the Gaussian filter (smoothing) for noise reduction, the finding of image intensity gradients, the reduction of spurious response to edge detection by applying non-maximum suppression, the detection of double thresholds, and finally the hysteresis based edge tracking. The final step suppresses all the other edges that are weak and not connected to strong edges. The resulting image is shown at the bottom-right of Fig. 2 with many edges detected at the aggregate boundaries and within the aggregate.

Finally, the soot primary particles are selected by the Circular Hough Transform (CHT) of the Canny edge image. The CHT implements a voting process to map image edge points into manifolds in an appropriately defined parameter space [43]. Peaks in the space correspond to the parameters of detected curves. The CHT requires two input parameters of the circle size range (minimum and maximum radius) and sensitivity. The primary particles detected by the CHT are overlaid on the Canny edge image as shown at the

bottom-middle of Fig. 2. The same primary particle boundaries are also overlaid on the original TEM image for the selected soot aggregate (bottom-left of Fig. 2).

Comparison Between Manual and Automatic Methods

One way to validate the newly developed particle detection code is its comparison to manually selected soot primary particles. The manual method is obviously arbitrary as it depends solely on one's visual inspection which can vary person by person depending on their level of understanding of soot structures. However, our previous work suggested that the selection process conducted by experienced operators (i.e. those with a clear understanding of soot primaries and their appearance on TEM images) can limit the fluctuations within $\pm 3.5\%$ [8]. Also, it was found that the size distribution of primary particles using a large sample volume with over 2500 selected particles shows near Gaussian distributions [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15], adding credibility to the mean value.

In Fig. 3(left), examples of the manual selection methods are shown in green rectangle boxes for selected aggregates from the Meiji CVC (noted "CVC" at the top) and UNSW diesel engine (noted "Engine" at the bottom). The images show that many circular primary particles stack up together to form an agglomerate of complex shape. Measurements for the diameter of these primaries were manually selected and overlaid on the aggregate image as green lines connecting one end to the other of primary particles. On the right of Fig. 3, primary particles from the automated detection method are overlaid on the same aggregates.

Some mismatches are seen in Fig. 3. For example, the automated method cannot detect a few primary particles such as primary 1 and 3. However, there are opposite cases that the automated method finds primary particles that are ignored in the manual method (e.g. primary 2 and 4). Overall, a good agreement is seen between the automated and manual methods while the automated method detects less primary particles than that of the manual selection. This is simply because the CHT requires a clear circular object whereas the manual selection is possible for incomplete structures depending on one's shape recognition.

Figure 4(top) shows the size distribution of 140 primary particles from the manual method together with the automatically detected 89 primaries. The results are from the selected TEM image of Fig. 3 (the Meiji sample [4,8]). At the bottom of Fig. 4, the results from the UNSW diesel engine are plotted for 6606 and 1636 primary particles from the manual and automated method, respectively. A total of five TEM images were processed [9,13] including the selected TEM image of Fig. 3 (the UNSW sample) to evaluate the performance of the new code for larger sample sizes. The size distributions of primary particles display overall a good match and the mean d_p show identical values of 17.9 and 16.4 nm for the CVC and the engine samples, respectively. It is also noticeable that the mean d_p is only 1.5 nm different between the Meiji CVC and the UNSW diesel engine cases, likely due to similar ambient gas and fuel injection conditions (see Tables 1 and 2). In comparison, this is much less than a difference of 5~6 nm caused by a closer sampling location from the nozzle [3] or higher injection pressure of 160 MPa [13].