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Application of an image processing-based algorithm for river-side granular sediment gradation distribution analysis

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Abstract. Determining grain-size and grading distribution of river-side sediments is very important for issues related to lateral embankment drift, river-side nourishment, management plans, and riverbank stability. In this regard, experimental procedures such as sieve analysis are used in regular assessments which require special laboratory equipment that are quite time consuming to perform. The presented study provides a machine vision and image processing-based approach for determining coarse grained sediment size and distribution that is relatively quick and effective. In this regard, an image image processing-based method was used to determine the particle size of sediments as justified by screening tests which were conducted on samples taken from the riverside granular sediments. As a methodology, different grain identification stages were applied to extract sediment features such as pre-processing, edge detection, granular size classification and post-processing. According to the results of the grain identification stages, the applied technique identified about 35% sand, 55% gravel and 7% cobble which is approximately near to the screen test results which were determined as 30% sand, 52% gravel, and 5% cobble. These results obtained from computer-based analyses and experiments indicated that the utilised processing technique provided satisfactory results for gradation distribution analysis regarding riverside granular sediments.

Keywords: geotechnics; grading distribution; image processing; particle-size analysis; sediments

1. Introduction

In the geotechnical discipline, granular materials are identified as soils/sediments with a grain size larger than 0.1 mm which have the ability to withstand heat fluctuations. They have formed by geological processes as residual or transported material after being issued from different rocks (Wood 1991) that are classified as coarse (larger than sand-size) and fine-grained materials (smaller than sand-size). Sediment particle size analysis and grading distribution determination is one of the important geotechnical parameters that is required in various civil, mining and geo-engineering related constructions, embankments, riverside improvements, coastal nourishments,

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coastal/riverside fortifications, river-bank stabilisations, etc. (Qiao and Fan 2014, Azarafza and Asghari-Kaljahi 2016, Azarafza *et al*. 2017, Xi *et al*. 2018, Chen *et al*. 2019, Krishna *et al*. 2019, Ye *et al*. 2019, Wen *et al*. 2021). Thus, in all geo-engineering constructions, the requirement of confiscating suitable geo-material grading evaluation is an important task. In order to investigate the sediment grading distributions, several procedures such as experimental and computer-based methods may be performed that are associated with certain advantages and disadvantages. Experimental tests require sampling, sample preparation, transferring and testing which is usually costly and time-consuming (Budhu 2010), whereas, computer-based methods are usually fast, cost effective, do not need sample preparation and are capable of large-scale grading determination which are deemed economical and time saving (Becker *et al*. 2018).

In experimental methods, evaluation of the grain size is through particle-size or sieve analysis tests (AASHTO T88, ASTM D422) which entail pouring the sedimentary soil mixture on the sieve series and shaking it. Depending on the sediment's grain size, the granular soils remain on the numbered sieves (categorised as meshes) which are recorded and plotted in relation to the residual percentage of soils remaining on the sieves as a 'grain-size distribution curve' from the analysed soil/sediment (Budhu 2010). This test is generally utilised for gravel and sand where larger-sized grains such as pebbles and cobbles are measured manually. Another method is the screen analysis that is commonly used in mining for separating materials from crusher or blasting operations by conveyor belts and lattice grids (stencils) which are based on particle-size analysis with the difference such that it involves more grain-sizes ranging from boulders to gravel. As well known, these measurements are time consuming and mostly require continuous review and control (Barnard *et al*. 2007). On the other hand, computer-based methods, due their processing features regarding to extract the relevant properties such as grading distribution and classifications have received more attention by researchers recently as a complementary method. Extensive grain size distribution can be detected by computer and image processing techniques from cobbles to clay and even microscopic imaging (Boggs Jr 2011). But the main application of the image processing in the geo-engineering field focuses on coarse-grained particles which can provide a more accurate sorting of particles and grain uniformity parameter evaluations (Buscombe 2008, Buscombe and Masselink 2009). Mainly, application of such image processing techniques in geo-engineering due to their accuracy in estimation of sediment characteristics and capability to be classified with a smaller error rate has received more attention from researchers of granulometry (Zomorodian *et al*. 2020).

Granulometry is one of the image processing-based methods that is used for the evaluation of grain size distribution and sediment grain geometry measurements by using superficial imaging technologies (Chávez *et al*. 2015). Image processing attempts to identify the size, shape and dimensions of the particles (Rubin 2004). In granulometric evaluations, probabilistic and statistical functions are used for an extensive expression of changes to reduce geometrical uncertainties (Charpentier *et al*. 2013) which can be considered in mining with a high production volume (where traditional methods have proved to be very costly and time-consuming) and has so far achieved many gains in grinding. Griffiths (1961) mentioned that the main geometric properties of sediments are shape, size and orientation, which can be calculated based on each grain's average diameter estimation in statistical communities to the total recording ratio (Cassel *et al*. 2018). The shadow portion is also evaluated by grading the particle ratio to the entire recorded area which is used for shadow region re-movement (Maiti *et al*. 2017). In such circumstances the background or shadow areas cause complications in the assessment which can be improved by observing certain conditions such as vertical imaging, light adjustment, lack of shadow areas, and the use of powerful imaging equipment (high-quality and high-resolution).

The first image processing application was used to determine the crushed stone distribution by Carlsson and Nyberg (1981). Latham *et al*. (2003) stated that the image processing application for sediment grain-size geometric determination provided an acceptable prediction. Faramarzi *et al*. (2013) determined a stone classification system to predict fragmentation resulting from explosion by the image analysis method. Liu *et al*. (2015) investigated the crushed stone/rock block size distribution in the block demolition extraction by using a probabilistic analysis. In addition, image processing techniques have been used to measure the rock block size in mines (Yarahmadi *et al*. 2015) or structural discontinuity networks in rock masses (Azarafza *et al*. 2019).

Dipova (2017) applied the image-processing technology and object-based method to identify grain size distribution and grain shape using simple apparatus, non-professional cameras and open-code software. He stated that the image analysis-based grain size distribution can be considered as a good comparative work with regular sieve-analysis distribution. Frydrych *et al*. (2019) used the granulomery method to extract the fluvioglacial coarse-grained sediments. The authors mentored the image processing technique to provide high speed and accuracy in grain size distribution analysis. Dill *et al*. (2020) used granulometry and morphometry procedures for gravel analysis or for sedimentography of coarse-grained deposits in meandering to straight fluvial drainage systems. The research provided accurate data regarding grain-size distribution of the studied sediments. Smith and Maxwell (2021) applied image processing and UAV-based photogrammetry techniques to provide multi-scale spatial distribution measurements on the outcrops of coarse-grained volcaniclastic and sedimentary deposits.

Image processing by using image enhancement, image segmentation, feature extraction, and structural identification, attempts to categorise the relevant/irrelevant features (Davies 2012), which are used to extract the sediment gradation properties (as relevant features) and remove the noise (as irrelevant features) with acceptable accuracy. The relevant features can be improved by using different filters in the pre-processing stage which aids a better analysis in the main processing stage. The filters provide a selective election to reduce the noise and highlight the relevant information to increase the accuracy of the pre-processing analysis in the next steps. The presented study has used this technique to identify and classify riverside granular sediment gradation distribution. In this regard, the three-stage processing consisted of pre-processing, main processing, and post-processing on basic images to extract sediment grain-size distribution.

2. Methodology of study

The study performed herein has utilised an image processing method to determine the aggregation size, dimensions and to prepare a grain-size distribution for coarse-grained riverside sediments by using superficial imaging. The main advantages of the image processing technique applications are listed as follows:

- Appropriate for geo-engineering works in regards to quick exploitation where traditional methods are time-consuming,
- Low cost in field investigation for aggregate depositions, riverbank nourishments, earth-dam embankment, sand washing, etc.,
- Possibility to be integrated with aerial imagery for the preparation of aggregation maps,
- Possibility to be used to trace and locate suitable sediment deposits,
- Capable to be coupled with other granulometry methods for grain-size and shape evaluation

in various scales,
- Grain analysis results can be used in grain size sorting and sediment characteristics such as screen test results,
- Rapid quantification and classification of the sediment grains based on size degradation features.

This method aims at identifying sediment grains, reducing and eliminating irrelevant features, solving the shadow, grain overlaps and classification data which is applied during a three-step pre-processing, main processing and post-processing stages. In this regard, it is initially necessary to provide the proper condition to take a basic image (e.g., establish appropriate natural or artificial sourced light, high-quality and good resolution imaging equipment, record all sediment levels and avoid any vibration, scale the image at a specific and/or appropriate scale, etc.). In such circumstances, one should try to avoid the shadows, mechanical and human errors. After preparing the basic image which is entered as the 'original image' as presented in Fig. 1, the image becomes sharper to be imported to the processing stages.

After preparing the original image, the image was improved by conducting filtering such as gray-scale filter, Gaussian, Lapasin, or Gaussian-Laplacein, etc which is referred to as the pre-processing stage. In this step, initial data extraction, such as edge identification and shadows were carried out to the extent possible, in order to reduce the error rate in the analysis. The pre-processing stage provided the 'basic image' which was used as a basis for the evaluations that

Fig. 1 Original images prepared from the studied sample

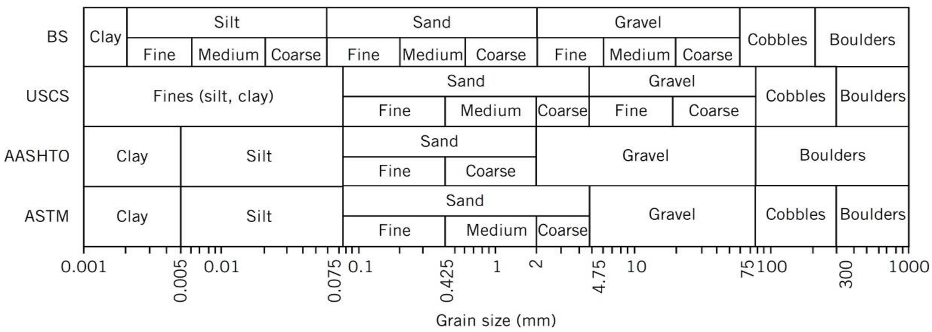


Fig. 2 Standard classification and sediment aggregation analysis scaling (Budhu 2010)

were performed in the next steps. During the main processing stage, sediment grains were evaluated in terms of shape and size and were classified according to the soil mechanical classification as shown in Fig. 2. This stage of the analysis process is referred to as the pre-trained step of which the machine uses for the previous findings based on the defined sediment geometric properties to classify the particles and to eliminate the irrelevant features. In this categorisation, a grain size greater than fine sand (0.1 mm) was considered, in other words, the algorithm limitation was for fine grained particles (less than 0.1 mm) and also, a particle size from fine to coarse sand (0.1-1.0 mm) associated with errors that originate from the shadow region and fine granulation. Hence, the main focus of the algorithm was coarse-grained sediment classification (more than 1 mm) where it should be noted that this error was related to the imaging equipment so that by increasing the capability of the equipment and reducing the imaging scale, smaller grain size could also be estimated. The output of this stage involved identifying the grain size using the average diameter of each grain (the average of the two main grain diameters), removing overlaps, classifying particles, determining grading distribution and shape. In the post-processing stage, the errors associated with the main processing stage were evaluated and reduced. If the error rate was greater than expected, the processing was resumed to minimise the error rates. Fig. 3 shows the applied process flowchart and Fig. 4 illustrates an example of the grain identification stages, overlap elimination, and grain classification. Fig. 4 is a simplified demonstration of a grain distribution analysis by using image processing which is classified in the pre-processing, main processing and post-processing stages.

During the main processing, the gradients were compared through overlapping which gave information on the shadow and noise in processing of the basic image. Korath *et al*. (2007) hae presented an algorithm to investigate overlapping objects in particle-size distribution. The method was built on the studies of Shen *et al*. (2000) and Honakanen *et al*. (2005). The work presented herein has used the method by Korath and his colleagues to evaluate the overlap phenomenon in particle-size analysis by image processing. To this end, median filtering and random noise removing was performed on the basic image. This filter is statistical filter which replaces

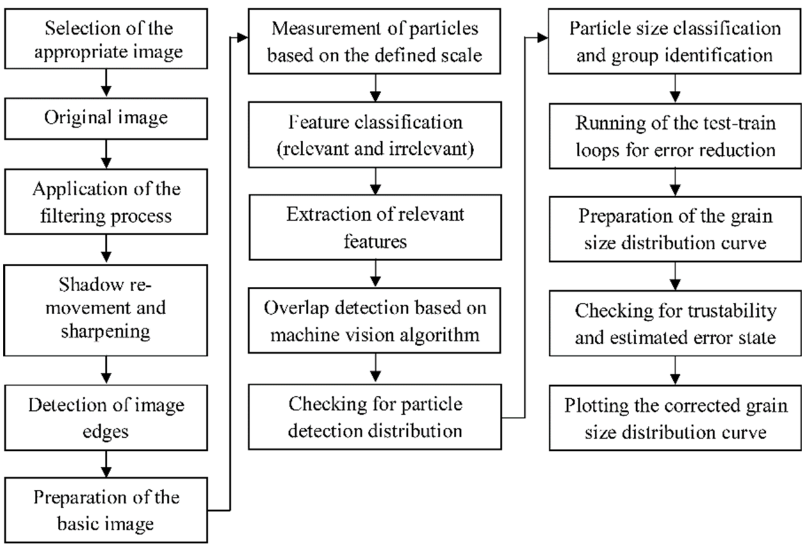


Fig. 3 General architecture of machine vision-based solution for trained grain distribution

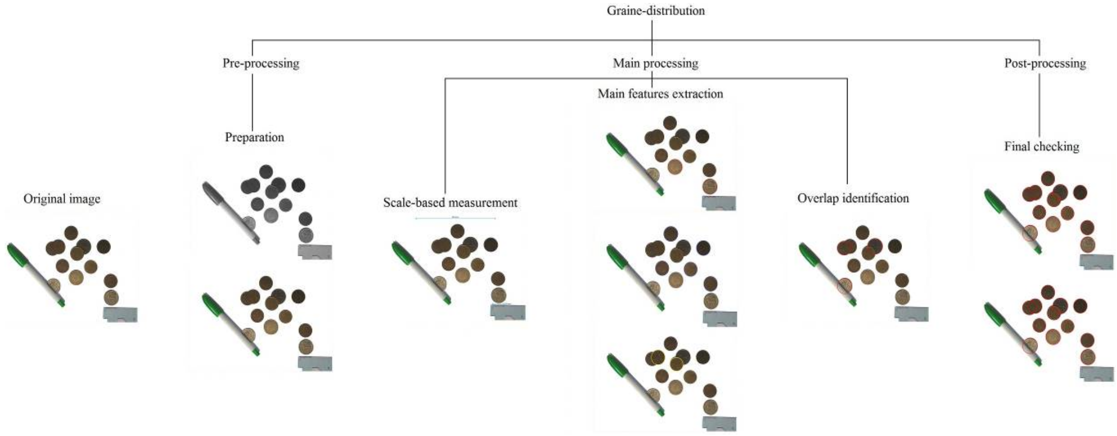


Fig. 4 An example for grain identification stages, overlap re-movement and classification

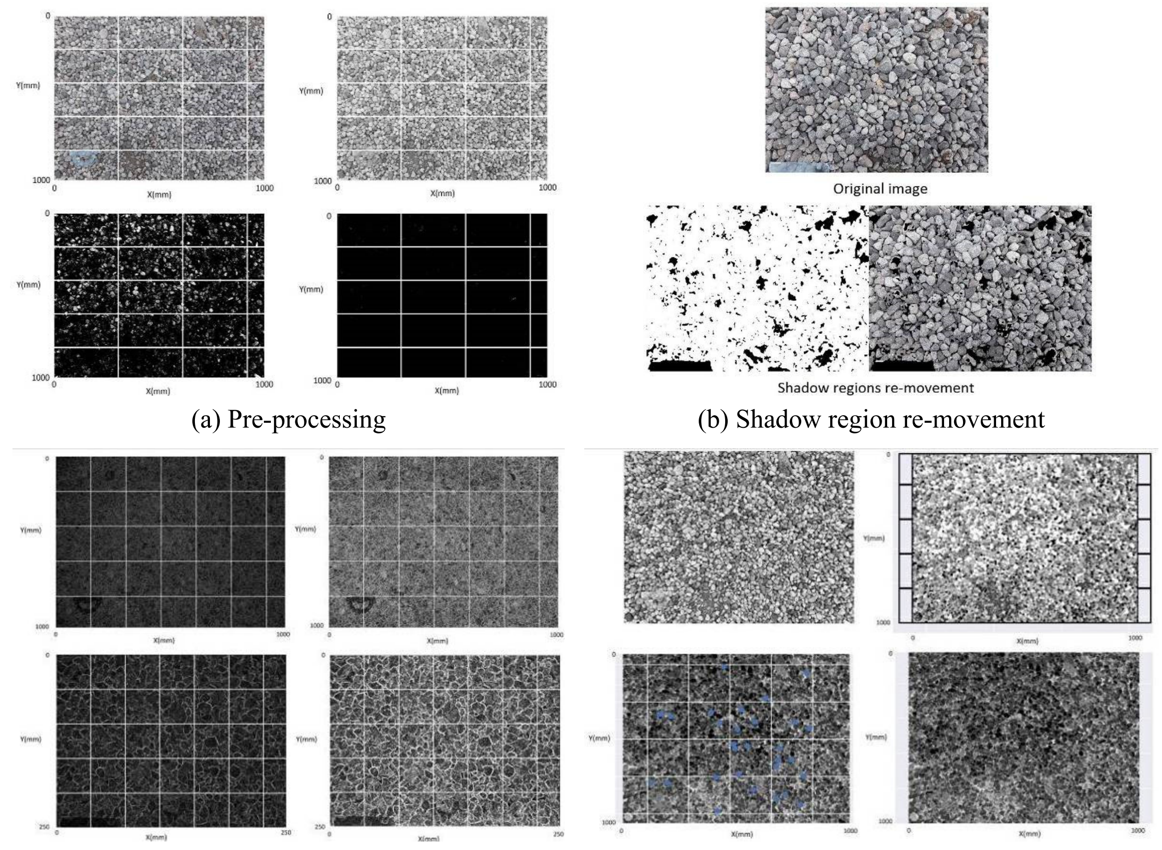
the value of a pixel by the median of the pixel values in a small neighbourhood (Gonzalez *et al*. 2010). Afterwards, the image was denoised and segmented by conducting the segmentation process and Otsu's method of global thresholding was used to classify the particles. The overlap area with intensity variations were characterised by regional-dips where less light was reflected from these sections (Korath *et al*. 2007).

3. Image processing-based grading analysis

In particle-size analysis, it is very important that image anomalies which are referred to as 'noise' be removed in preliminary conditions as early as possible (Maiti *et al*. 2017). These anomalies affect the shape, grain size and sediment grading distribution. In this regard, the base image must be pre-processed to filter the possible noises. In other words, there is an approximation and range operation, so that the obtained value for each output image pixels are corrected by applying one or more filtrations to the pixels that are located in the vicinity of the input pixels (Solomon and Breckon 2011). To this end, some filtering operations are performed on the image such as gray-scale, Laplacian, Laplacian-Gaussian, gradient, and gradient orientation discrete filters in the pre-processing stage. These filtrations are very important to prepare a suitable basic image to conduct the main processing, edge detection, and to extract the relevant features. If the sediment grains are to be considered as an image, a sudden change in the intensity concentration in the boundary regions is considered to be severity boundaries. These boundaries can be used as geometric margins which are capable of estimating the size, shape, and average diameter. Such implementation (discrete derivation) causes another image of the initial image to be obtained; where the size of the pixels at the edge position is larger than the size of the other pixels. Therefore, using the position of these pixels, the objects or elements of the image become discrete and the edges are identified (Gonzalez *et al*. 2010) so that it is possible to identify the separated grains of the sediment by considering the discontinuous space between the grains, the possibility of determining the grain size and hence to estimate the average diameter of the grains and their classification.

Fig. 5 shows the pre-processing for the original image to convert into the basic image. As can be seen in Fig. 5, the initial image has been substantially improved and the intensities were considered in the positive and in the negative sections (which indicate the deletion of the shadow regions). The output image of this stage was used as the basic image for performing the main processes. The main processing establishes various feature extraction functions such as edge detection, geometric margin evaluation, average diameter calculation, etc. The final stage contains the error reduction procedure to minimise the noise rate in processing. In the post-processing stage by selecting random points in the basic image, the rate of the predictability is estimated and the error function (cumulative probability and error percentage) of the selection is calculated. If the obtained error for the selected points shows a declining trend, this indicates that this phenomenon can be used to evaluate errors. According to the error analysis of the study, the training stage error rate is reduced to less than 0.3, which is acceptable.

In general, the image processing technique is an intelligent instrument which evaluates the environment and selects the elements, where it counts, separates and classifies objects, individuals, and so on Sonka *et al*. (2014). Therefore, through using these methodologies, it is possible to limit the extracted features for specific situations. By this approach, the main focus is on a certain category of features, where in this study the dimensions of the grains, the geometry of grading and



(a) Pre-processing (b) Shadow region re-movement

(c) Edge-detection operations (d) Environment detection

Fig. 5 Results of image pre-processing operations for sedimentary grains

the average size of the grains along with other characteristics are ignored. The processing technique seeks to reduce the search space and provides areas that are appropriate to the original elements and focuses on identifying those parts (Uijlings *et al*. 2013). This can be very convenient in identifying sedimentary grains that are located in smaller grain fields and for increasing the focus for selective searches between the grains. Another issue in the field of grains is the overlap of grains, which can be detected by using a method such as the phase coding method or the two-stage method (Pont-Tuset *et al*. 2017). It should be noted that the above-mentioned methods have been introduced for classical searches. Fig. 6 illustrates the general architecture of problem solving for trained sedimentation. As seen in this figure, learning algorithms increase car perception in the separation, classification and assortment of sediment grains. This issue plays an important role in estimating sediment types, sediment geotechnical parameters and grading coefficients.

The purpose of the method presented herein is to determine sediment classification, the percent dominance of aggregates, grading coefficients, grain sufficiency, and degree of uniformity. By using the classification principle, the gradient coefficients such as the percentage of grains (d_{10}, d_{30}, d_{50}, d_{60}, d_{90}), uniformity coefficient (Cu), curvature coefficient (Cc), etc., were determined where d_{50} represents the smaller amount of sediment particles of that amount on the grain size distribution curve. For other values, it is defined as 10%, 60%, and 90% finer than that value (see Fig. 2). The gradient was calculated based on the medium size and the limiting sieve size. Thus, the uniformity coefficient ($Cu = d_{60}/d_{10}$), the mean grading (d_{50}) and curvature coefficient ($Cc = d_{30}^2/d_{60}\times d_{10}$) were easily estimated. Fig. 7 shows the results of the utilised method on the basic image for sediment grain size analyses. Post-processing was implemented to reduce the error or noises after the main analysis. In this stage, the results of the analysis were controlled by the learned strategies regarding the continuity and consistency. In the event of any inconsistency, the analysis phase has been restarted from the beginning and continued until consistency where the learned data was achieved. This was pursued in order to increase the accuracy, precision and for recalling the calculations which affect the results.

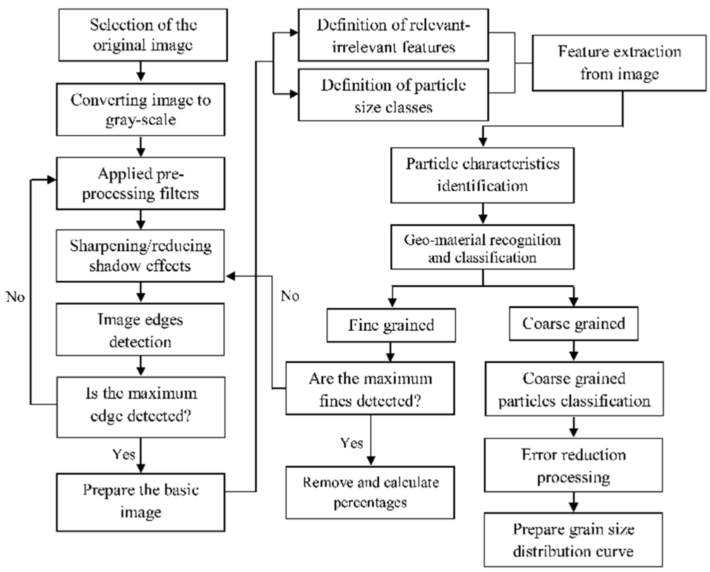
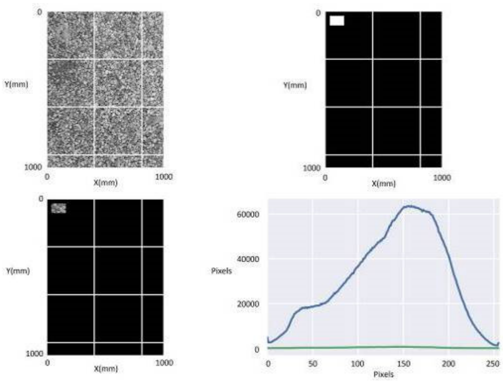
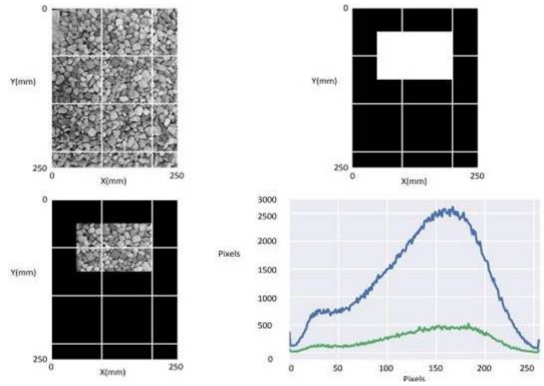


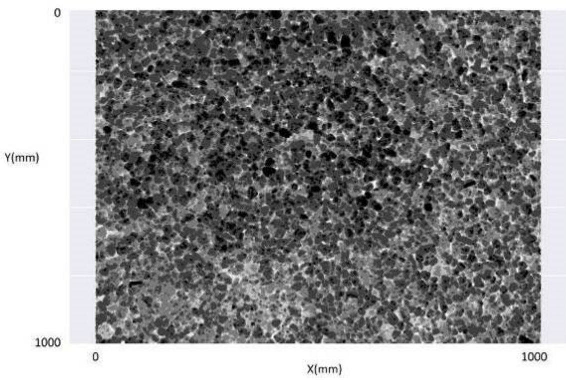
Fig. 6 Mesh grid of the topographic model



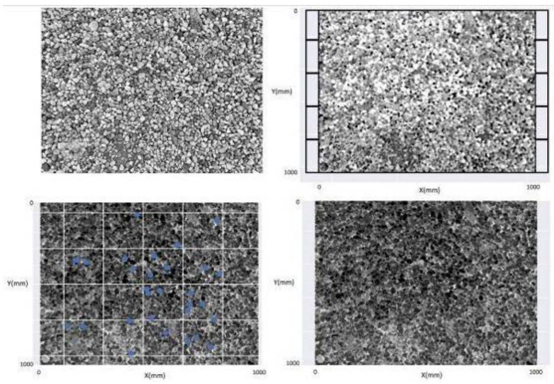
(a) Cell definition



(b) Body detection



(c) Overlapping particles detection



(d) Particle type recognition

Fig. 7 Sedimentary particle pattern recognition

4. Interpretation and model justification

4.1 Screening test and grading analysis

In order to evaluate the accuracy and the efficiency of the applied model in this study, the sediments have been analysed by sieve analysis which is fully described by the American Society for Testing and Materials and the American Association and State Highway and Transportation procedures (AASHTO T88, ASTM D422). In this laboratory test, the sediments are mixed and placed on a series of sieves and shaken within a specified time interval. Each of these sieves has a certain scale known as mesh number. After the completion of the tests, the weight of the residual material is recorded. The results are expressed on the basis of the weight percent and are used to describe the aggregate conditions of the sample, which appears to be a gradation curve (Budhu 2010). The main aspect of the sieve-analysis distribution is to provide the geometric properties of the soil / sediments against the percentage of the weight passing through standard sieves that are designed in special sizes. In fact, the volume passing through each sieve indicates the weight of the grains smaller than the mesh, which has a certain size. This sieve is classified ranging from a large to fine sized sieve. As much as the soil particles passes through these sieves and the lower the sieves, the finer is the soil. An overview of the test and the sieve used in these experiments are

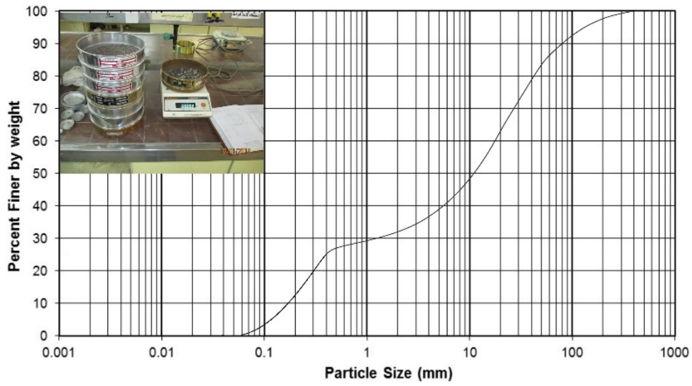
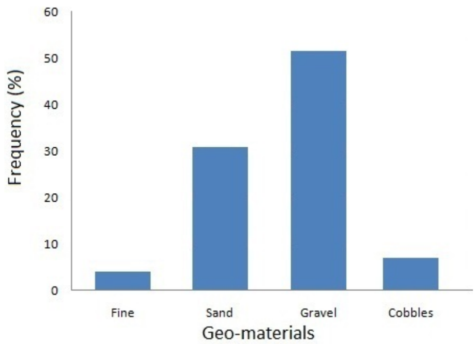
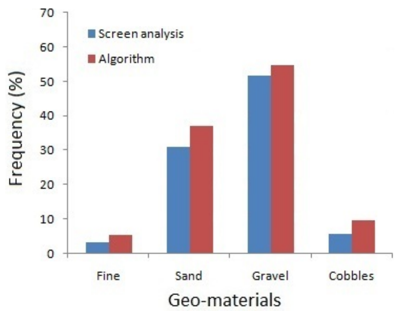


Fig. 8 Experimental results of sediment grain size distribution

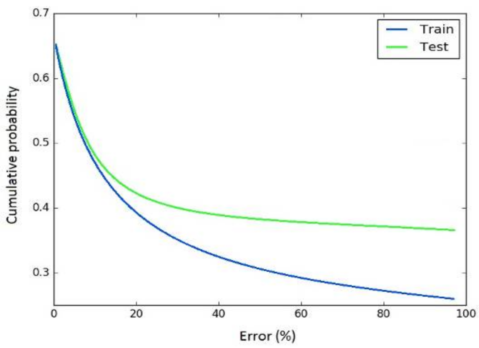
presented in Fig. 8 where values larger than 10 cm were separated and after the dimension and shape measuring, these results were ultimately combined with the sequencing analysis results.



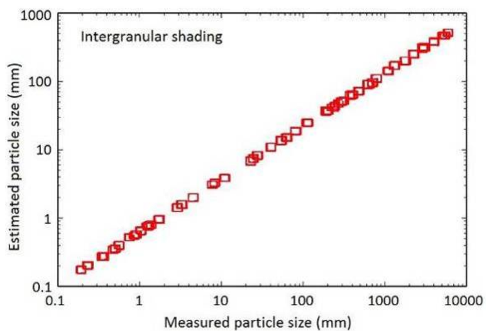
(a) Granular materials percentage from the studied sediments



(b) Dominant type of granular materials and classification



(c) Cumulative probability and error percentage



(d) Effect of intergranular shading

Fig. 9 Results of granular material percentage and grain type evaluation

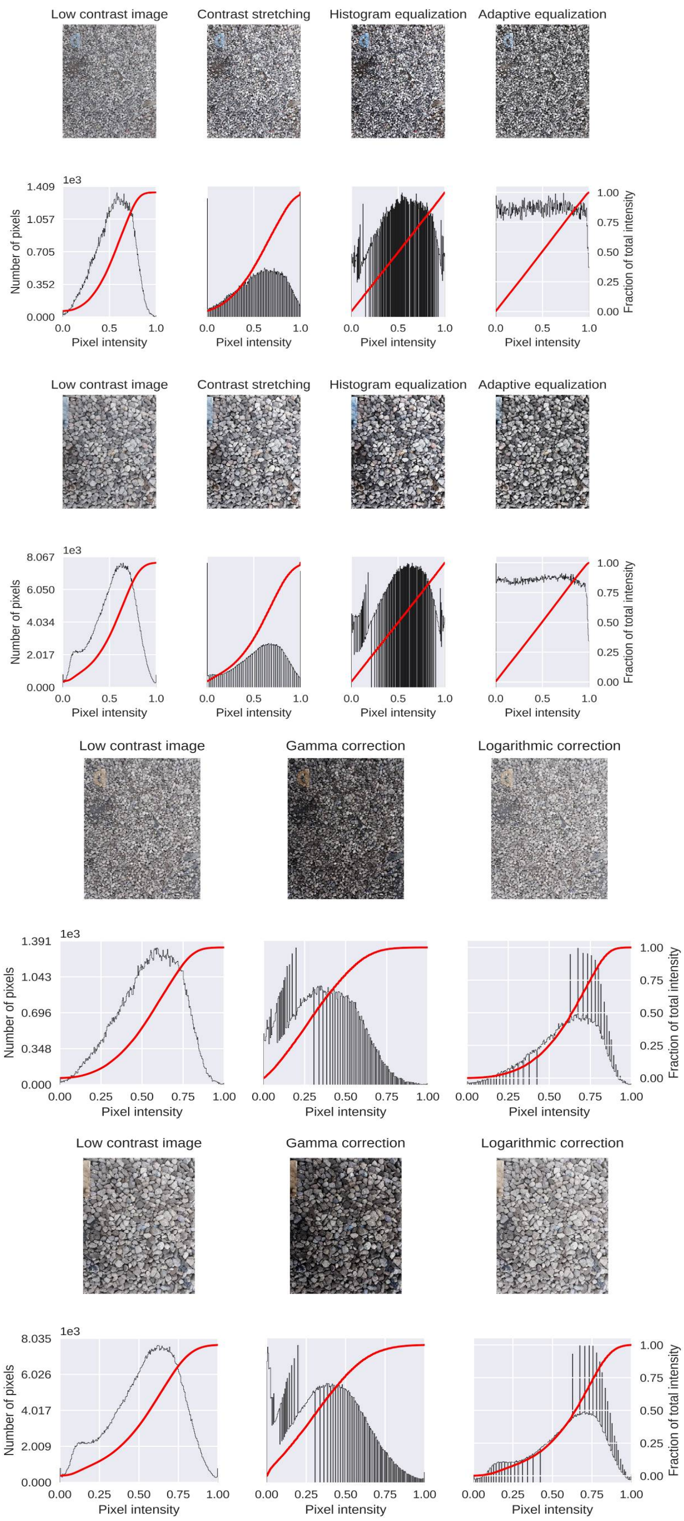


Fig. 10 The spectral correction of sediment concentration

4.2 Comparative interpretation of the grading analysis results

The main goal of the applied method was to identify and estimate the dimension, shape, size and distribution of the coarse-grained sediment which is compared with the sieve analysis test. The grain percentage (as determined by the instructions given in Fig. 2), the particle type dominance (aggregate distribution and main range), sediment geotechnical data, gradient coefficients as determined through the proposed algorithm are presented in Figs. 9 to 11 as well as in Table 1. Fig. 9(a) presents the applied method results for classification of the studied sediment's particle-size distribution. According to this figure, the obtained results showed 35% sand, 55% gravel and 7% cobbles. The comparative results of the used method and experiment is illustrated in Fig. 9(b). According to the screen test, the results indicated 30% sand, 52% gravel, and 5% cobbles and it seemed evident that the image-processing based method was reasonably accurate. Fig. 9(c) provides the cumulative probability and error percentage curves that were conducted on selected random points on basic image during the main processing which presents the error status in the analysis procedure. These selected points are classified as test-trained data-sets and analysis by using supervised learning to estimate the loss function. The results obtained by utilising predictive analysis and regression correlation are illustrated in Fig. 9(d). Fig. 10 illustrates the main processing stage which is used to classify the pixel intensity variations on basic image based on various correction functions. The results of this stage were used to categorize grain-size and grain distribution. In the post-processing step, the analysis error and appraisal accuracy was estimated by sediment particle-size variation as shown in Fig. 11. According to this figure, the method's performance in size detection increased with increased grain size. The estimated error percentage was reduced from 8% to 0.01% for grains with a size of 0.01 to 1000 mm. The reason for this was that, as the grain size increased, the pixel changes in the images became more pronounced, resulting in more accurate particle detection. The use of more accurate equipment to examine finer grains would increase the accuracy of the assessment.

As can be seen from these figures and table, the proposed algorithm was able to track the size and distribution of the coarse sediment. In fine grained soil analysis, the shadow area and undetected area mostly overlapped leading to a reduction in the measurement accuracy which may be improved by utilising more powerful equipment for imaging and by reducing the scale. In addition, the used method had a lower cost, speed, and consumed less time to obtain the results.

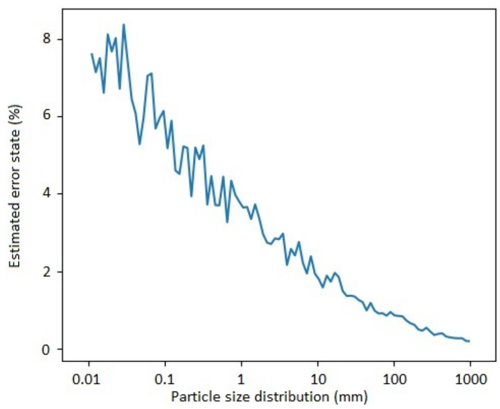


Fig. 11 Effect of error reduction on sediment grading evaluation (appraisal accuracy)

Table 1 Comparative evaluation between the algorithm and empirical results (basis of comparison is USCS/Unified classification)

Parameters		Algorithm	Screen analysis	Description
Gradient coefficients	D_{10}	0.23 mm	0.18 mm	High precision
	D_{30}	1.21 mm	1.10 mm	Good precision
	D_{60}	10.6 mm	10.8 mm	High precision
	D_{90}	83 mm	80 mm	High precision
Mean grading (D_{50})		10.2 mm	10.3 mm	High precision
Curvature coefficient (Cc)		0.600	0.622	High precision
Uniformity coefficient (Cu)		46.086	60	-
Sediment surrounding		High	-	-
Particle size distribution curve		Poorly graded with gaps	Poorly graded	High precision
Material classes		Sandy gravel with fines	Sandy gravel with fines	High precision

Amongst other advantages of the used method were to cover regular screening techniques to resolve the degree of smoothness estimation which can be used in the geological history investigation of the sediment. According to the results of the study, the grain size distribution of the granular sediments for the Riverside project appropriately covered the results of the sieve analysis test which verified the proposed algorithm. In addition, the results of the proposed algorithm were obtained considerably faster than the experimental methods for the proper approximation of the sediment grain size and grading distribution.

5. Conclusions

The particle-size analysis in geotechnical projects that especially involve sediments and soils is very important to characterize the materials. In this regard, experimental and computer-based methods were introduced. The experimental methods such as sieve analysis is well known in the geo-engineering field and the computer-based methods can be classified as granulometric procedures. The general structure of granulometric methods are utilised in the evaluation of grain properties and the distribution of the size, dimensions, and shape of granular sediments, in particular coarse-grained soils. The method was established based on surface imaging that generally requires specialised advanced equipment. In granulometry, application of image processing techniques is fundamental in investigating the particle-size distribution in soil materials. Application of the image processing technique proves to be necessary when large volumes of grading distribution evaluation is needed or when time is limited.

The presented study has used an image processing approach to identify, categorise and determine the dominant percentage, and to estimate the sedimentary grain dimensions, shape and size. Utilisation of such studies provide a proper vision in the early studies of geotechnical projects and reduce the cost of the initial studies. In addition, it can be of help to achieve proper precision, high-speed and the sediment grading distribution. In this regard, the image processing-based method which is an alternative method to the screen test was implemented to characterize the riverside granular sediments. The method was verified by experimental grain-size and grading distribution tests described by AASHTO T88, ASTM D422. According to the obtained results, the applied method estimated about 35% sand, 55% gravel, and 7% cobbles which was concordant with the screen test results that estimated 30% sand, 52% gravel and 5% cobbles. A comparison of the results of the model and experimental results revealed that the image-based model was reasonably accurate.

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