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TECHNICAL NOTE

CRIMINALISTICS

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Automated Texture Recognition of Quartz Sand Grains for Forensic Applications*

ABSTRACT: Quartz sand surface texture analysis has been automated for the first time for forensic application. The derived Basic Image Features (BIFs) provide computer-generated texture recognition from preexisting data sets. The technique was applied to two distinct classification problems; first, the ability of the system to discriminate between (quartz) sand grains with upturned plate features (indicative of eolian, global sand sea environments) and grains that do not exhibit these features. A success rate of grain classification of 98.8% was achieved. Second, to test the ability of the computer recognition system to identify specific energy levels of formation of the upturned plate surface texture features. Such recognition ability has to date been beyond manual geological interpretation. The discrimination performance was enhanced to an exact classification success rate of 81%. The enhanced potential for routine forensic investigation of the provenance of common quartz sand is indicated.

KEYWORDS: forensic science, quartz grain surface texture analysis, provenance, Basic Image Features, encoding, automated recognition

Quartz grain surface texture analysis (QGSTA) by scanning electron microscopy (SEM) is a well-developed analytical technique for palaeoenvironmental reconstruction (1–3). Quartz is a mineral that is resistant to both physical and chemical attack in the environment and is therefore a highly ubiquitous component of soils and sediments. The history of a quartz grain can be established through the analysis of the shape and surface features (both mechanical and chemical) observable on that grain under high magnification (1). Such information can indicate provenance, a highly useful attribute in forensic investigations where it may be possible to collect soil and sediment evidence from a crime scene, alibi scene, suspect, or victim (4,5). The comparison of such soil evidence may help to exclude suspects from an investigation or indeed confirm or refute an alibi (6,7). Owing to the visual nature of this technique, it is a highly valuable form of analysis for forensic soil/sediment samples as it does not require the homogenization of the sample prior to examination (as is often the case with other analytical techniques, e.g., elemental analyses, color, and particle size analysis). This enables the QGSTA to identify when a soil sample is composed of a mixture of quartz derived from multiple sources (8,9). Thus, meaningful and accurate comparisons can be made between samples derived from anthropogenic sources that are likely to be of mixed source (e.g., footwell of a vehicle) with natural samples (e.g., grave site) and this dramatically reduces the possibility of false exclusions (4).

However, only recently has a classification system for these attributes of quartz grains been articulated for forensic application by Bull and Morgan (4). This work also presented for the first time an embryonic database of some 30,000 quartz sand grains from England, which enables the comparative rarity or ubiquity of a quartz grain "type" or group of types to be established. The classification system presents four main types of quartz grain (at the first order): angular grains, rounded grains, metamorphic grains (those exhibiting strain-induced shapes), and diagenetic/chemically modified grains (designated A, B, C, and D, respectively; see Fig. 1). Each first-order type is subdivided into a second-order classification (A1, A2, B1, B2, etc.) that relates to environmental features such as glacial, eolian, subaqueous, or diagenetic textures present on the grain surfaces. Third-, fourth- and fifth-order subdivisions are primarily concerned with whether the quartz grain edges are abraded or rounded (for further details, see Bull and Morgan [4]). This work has highlighted the accuracy and power of the exclusionary and diagnostic capabilities of this technique for forensic soil/sediment analysis.

Forensic geoscience investigations aim to either establish a source of material in a "seek and find" manner or compare samples from known sources (victim, crime scene, suspect, etc.) to establish whether they have derived from a similar provenance. In this paper, we concentrate on the diagnostic surface textures of upturned plate features that are found only in sandy desert environments and are formed following free-grain collision of semi-rounded to semi-angular grains. Recent cases of suspected terrorist

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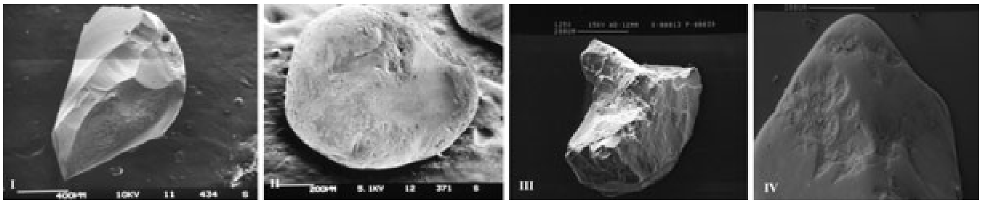


FIG. 1—*Angular grain of glacial origin (I); Rounded grain of aeolian origin (II); Metamorphic grain (III); Diagenetic grain (IV) designated A, B, C, D, respectively.*

activity have required the search for these features on quartz recovered from clothing belonging to persons entering the United Kingdom. QGSTA is able to establish whether the sand derived from the alibi site suggested by the suspect or whether the materials have derived from global sand sea environments or indeed from other very different environments.

However, a core issue for this technique is its reliance on the operator to classify each quartz grain individually (normally 50 grains per sample), which is therefore a time-consuming process. It is generally reserved for serious crime cases that have the resources available to commission such work. If this highly diagnostic analytical technique is to be used more widely and become more accessible to forensic investigators, it is essential that the time required for analysis is reduced.

This paper presents a preliminary study into the viability of applying automated computer recognition technology (similar to that used in face, texture, and object recognition systems) to act as a filter to exclude quartz grains within a particular sample on the basis of dissimilarity. Such a tool would decrease the number of quartz grains requiring individual analysis and therefore the amount of operator analysis time required for each sample. Previous work on the classification of quartz particles has concentrated either on the description of the silhouette shape of individual particles (10,11) or on the textural properties of surfaces (12) or bulk samples (13,14). Furthermore, no previous system has classified particles into a forensically suitable classification system.

Despite recent advances in texture recognition systems (15–19), there are no recorded instances of these systems being applied to forensic grain or particle analyses. Basic Image Features (BIFs) (20,21) have been used to provide excellent results for texture recognition when using standard texture data sets in the field of computer vision (16), and this paper presents the first application of this technique to QGSTA for forensic use. Therefore, the system presented here utilizes a well-established method in Computer Vision to compute a BIF-based texture description of the surface feature (for an example, see Fig. 2). The system then seeks to exclude grains on the basis of difference rather than to associate or "match" quartz grains on the basis of similarity and thereby adheres to the primary principle of the forensic geoscience philosophical framework of exclusion (8,9).

Methodology

A full and detailed methodology of the encoding process utilized for this work is presented by Newell et al. (22). Two problems were addressed. The first related to the discrimination between quartz grains with upturned plate features (indicative of eolian environments) and those without these features. Forty-seven quartz grains that had been impacted against each other under eolian conditions of known velocities under controlled laboratory conditions (see Marshall et al. [23]) were subsequently imaged under SEM. Images were taken of specific areas of each of the 47 grains where upturned plate features were identified resulting in 266 images that comprised the first data set of upturned plates (UP). A second data set was constructed from 41 quartz grains that exhibited other textual features, which resulted in 237 images of "not upturned plates" (NUP). Figure 3 provides sample images from each data set.

The second problem addressed (building on the successful resolution of the first) concerned whether or not the recognition system was able to identify the specific energy level of formation of the UP identified on the 47 grains as presented in Marshall et al. (23). The UP data set was divided into six categories that related to the velocity of the grain collision that resulted in the upturned plate texture as presented in Fig. 4.

For both problems, images were encoded using BIFs (20,21), a system that assigns each location in an image to one of seven classes according to local symmetry type. The algorithm, which is given below, uses a bank of six derivative-of-Gaussian filters to assign the type as either *light line on dark*, *dark line on light*, *light rotational, dark rotational*, *slope*, *saddle-like*, or *flat*. The algorithm takes two parameters, the scale parameter, σ, that determines the size of the filters and the threshold parameter, ε, that determines the likelihood of a location as being classified as *flat*. The BIF encoding is invariant to rotation and reflection.

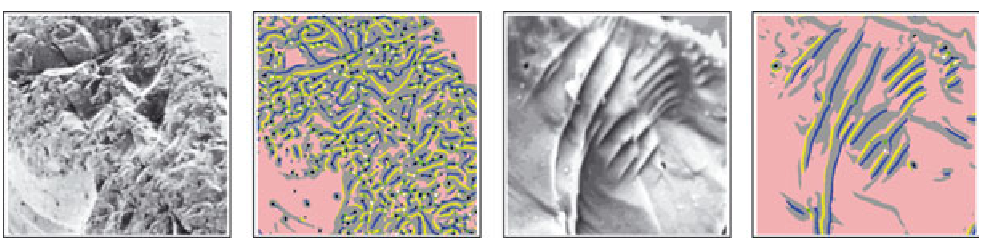
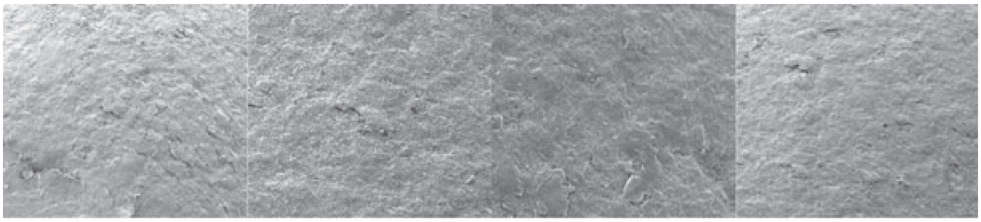
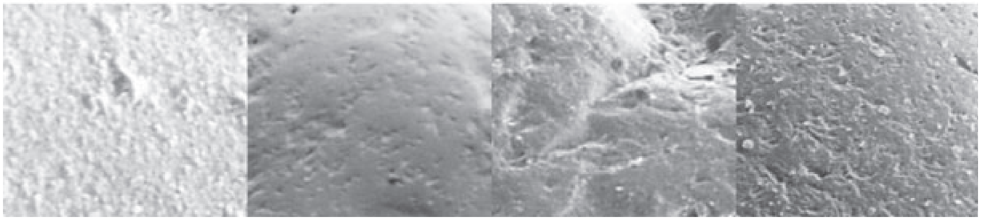


FIG. 2—*Two different quartz grains analyzed into Basic Image Features (BIFs). The textural differences between the grains are clearly apparent in the arrangement of the seven types of BIF.*



Upturned plates (UP)



Non upturned plates (NUP) (Chemical etching, v pits, chemical, chemical)

FIG. 3—*Examples of images for the two data sets UP and NUP.*

The BIF calculation:

- Measure filter responses c_{ij} to an (i, j)-order derivative-of-Gaussian filter, and from these, calculate the scale normalized filter responses $s_{i,j} = \sigma^{i+j} c_{i,j}$.
- Compute $\lambda = s_{2,0} + s_{0,2}, \gamma = \sqrt{\left(s_{2,0} - s_{0,2}\right)^2 + 4s_{1,1}^2}$
- Classify according to largest of

$$\left\{ \varepsilon s_{0,0}, 2\sqrt{s_{1,0}^2 + s_{0,1}^2}, \pm\lambda, (\gamma \pm \lambda)/\sqrt{2}, \gamma \right\}$$

To increase the discriminative power of the system, BIFs can be combined across scale to produce features known as BIF columns (16,22). To do this, BIFs are calculated at a range of geometrically spaced scales and stacked, at each location, to create a single feature. Two further parameters are introduced in this process, the number of scales used and the ratio between the scales. Previous work has shown that, for texture applications, four scales are sufficient, and the optimal threshold parameter is 0, meaning that the *flat* class is unused (16). This results in a set of 6^4 (= 1296) possible BIF column types.

Finally, BIF columns are counted across the image and divided by the total number of features to produce a normalized histogram that is invariant to rotation, reflection, translation, and the size of the image. These histograms can be then used to build a *k* nearest neighbor (kNN) classifier, where each test image is compared with all training images, and a classification is made according to the *k* most similar images.

Results

Upturned Plates and Not Upturned Plates

The first problem utilized multiple images from each of the 47 quartz grains as described previously. As the underlying problem involved the identification of a characteristic of each grain and the data set contained multiple images for each grain, a scheme for combining information from different image classifications had to be chosen. Three different schemes were tested. First, a single image was used to classify the whole grain, which is referred to as the *Without Pooling* scheme. Second, each image from a grain was classified individually and the majority classification was assigned for the grain. This is referred to as the *With Pooling* scheme. The third scheme, referred to as *Global Histogram*, took the mean of the histograms for each image for the grain and then classified this single encoding.

All images were encoded using BIF column histograms. To make best use of the images available, a nested leave-one-out system was used. To do this, a test image was first selected from the data set, and the other images from the same grain were discarded. Another image was then selected for validation, with the remaining images from that grain being discarded. The remaining images were then used to build the kNN classifier, which was then used to classify the validation image for different parameter values. This process was then repeated for all possible validation images and an optimal set of parameter values were selected, which were then used to classify the test image. This process was then repeated for each possible test image and the mean rate of correct classification was then calculated. The results are shown in Table 1 where the results are quantified as the average of the correct classification rate for UP grains and NUP grains. The best-performing scheme achieved a success rate of grain classification of 98.8% (equivalent to classifying all but one grain correctly) illustrating that the system performs better when multiple images of an individual grain are considered.

Energy Level of Formation

To ascertain the general discrimination power of the system to discriminate between grains exhibiting upturned plate features derived from different energy regimes, images were encoded as described above, and the same three schemes were used. However, as for this problem, there were fewer images per class than in the UP problem, it was not possible to devise a stable validation process and the parameter values were set in advance.

From the first analysis, it became apparent that the system was not able to discriminate effectively between the higher energy impacts (14–20 m/s) with results (across all three methods) of 41–71%. The images were therefore reclassified into a revised set of four classes (4, 8, 11, 14 + m/s) and then the same three methods were used to test the differentiating power of the system (see

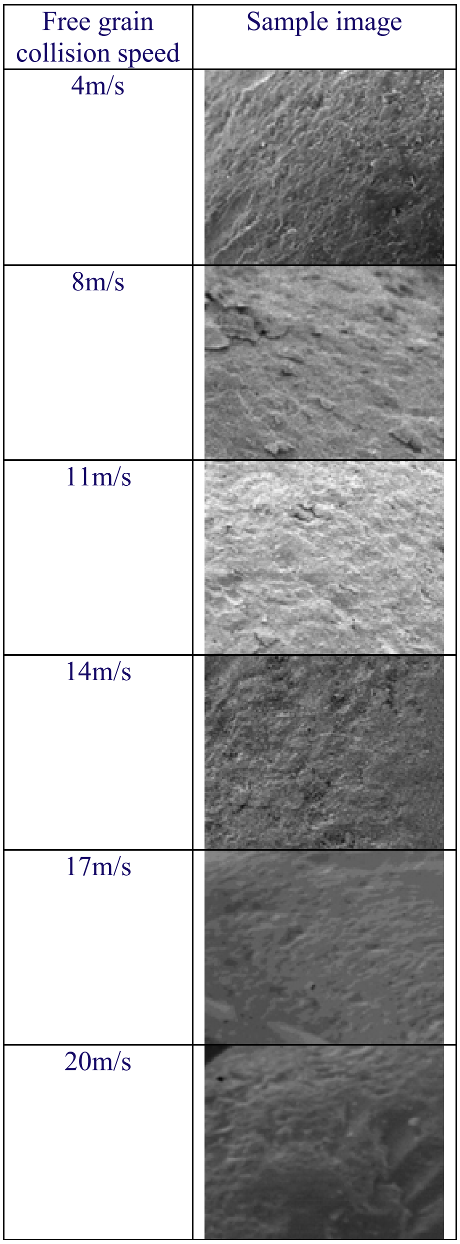


FIG. 4—*Images of upturned plates derived from different energy conditions.*

TABLE 1—*Performance for the upturned plates discrimination task.*

Scheme	Discrimination Performance Score (%)
Without pooling	95.0
With pooling	98.8
Global histogram	98.8

TABLE 2—*Performance for the energy level of formation task.*

Scheme	Exact (%)	Within 1 Class (%)	Within 2 Classes (%)
Without pooling	69	90	100
With pooling	81	96	100
Global histogram	78	92	96

Table 2). To classify grains according to the energy level of the upturned plate feature, formation presents a difficult task for the human operator and this is reflected in the performance of the BIF column system where it was unable to differentiate successfully between the higher energy levels from one another. However, with the number of classes reduced to four, the discrimination performance was encouraging with the top-performing scheme achieving a rate of 81% exact classification and 96% within an error of one class. As found previously, the system performed best when multiple images from each grain were used. These results were generated with a relatively small data set, and it is anticipated that the performance of the system for the discrimination between different energy levels could be improved with a larger training data set.

Forensic Implications

This preliminary work indicates that there is great potential for the BIF column system to be used in the automated discrimination of quartz grain surface textures. The successful discrimination of quartz grains on the basis of the surface textures has many implications for a number of different aspects of forensic investigation.

Environmental Reconstruction

The identification of the production of different eolian surface textures in relation to different free-grain collision speeds has only very recently been identified under simulated environmental conditions (23). The discrimination between upturned plate features by speed of formation has not been attempted using environmental samples by an operator. The automated recognition software therefore presents a new development in the discrimination of quartz grains based on their surface textures as it has the potential to discriminate grains from a similar environment that have undergone different prevailing eolian conditions, thus further refining the power to assign more accurate provenance of sediment samples. Further discriminatory power is an exciting development for both the environmental reconstruction field and also indicates further potential for the discriminatory power of automated texture analysis for comparative criminal forensic investigations.

Quartz Grain Surface Texture Analysis

In addition to furthering the diagnostic capabilities of QGSTA, this development indicates that there is potential to reduce the amount of operator time required to undertake such analysis on forensic soil/sediment samples. Currently, approximately 50 grains are individually analyzed and assigned a grain type by an operator. An experienced operator can undertake this task in 30–60 min. This present methodology has the potential to be able to exclude the grains that are clearly different to those identified in a comparator sample and thus the operator simply needs to manually look at those remaining grains that were not excluded by the software to derive exclusionary conclusions to assign a grain type. The process takes the computer a matter of seconds to undertake this analysis. This will enable more grains to be analyzed in each sample (sample size permitting) and also enable more samples to be analyzed in a shorter period of time. All of these aspects will increase the availability of this forensic technique as it will reduce the turn around time for analysis and therefore the associated costs.

This preliminary study has demonstrated the capabilities of this system to identify one specific grain surface feature. This success indicates that the system is capable of further refinement to be able to identify other environment specific surface textures and ultimately specific quartz grain types (see Bull and Morgan [4]) for more comprehensive analysis of soil/sediment samples.

Trace Evidence Particulates

The automated recognition tool using the BIF column system to encode texture used in this example has been applied without any major adjustments or tuning from previous formulations (22). This indicates that this system of encoding texture has great potential for successful application in other areas of trace forensic analysis. Natural extensions of this work could be to apply this technique to other mineral types, metallic particulates, pollen grains, diatoms, and perhaps even hairs and fibers. It is however of paramount importance that any work in this area is sufficiently rooted in the forensic science philosophical framework (8,9) to ensure that the analysis is appropriately undertaken in the first place and then also interpreted and presented in a meaningful and accurate manner that is able to provide robust intelligence and evidence.

Conclusions

This study has demonstrated the potential for a texture recognition tool to enable the automated delivery of results from forensic QGSTA by an exclusionary mechanism that can be estimated to increase sample turnaround time significantly. The potential for such a tool has implications for both this form of geoforensic analysis and the analysis and interpretation of other types of trace evidence that may be pertinent to criminal or security investigations.

The finesse of the technique to be able to identify subtle differences between the same broad texture type (in this case, UP formed at different wind speeds) expands the previous capabilities of forensic QGSTA. This development has potential for forensic investigations particularly in the field of counter terrorism and defense as it will enhance the comparative capabilities of the technique, and thus, its ability to distinguish further between different eolian environments which may be pertinent to an investigation.

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