Texture discrimination of volcanic ashes from different fragmentation mechanisms: A case study, Mount Nemrut stratovolcano, eastern Turkey

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Abstract

Multicondition-driven mechanisms may produce pyroclastic deposits varying in fundamental properties such as dispersal, grain size, vesicularity and morphology of juvenile clasts, and the abundance of lithic or “wall rock” ejecta (xenoliths). Volcanic ash particles from different fragmentation mechanisms have different surface textures and morphologies. The analysis of the volcanic clast shape remained largely qualitative. A new method for ash particle characterization based on quadtree decomposition and surface gradient analysis is introduced. The approach is applied for assessing fragmentation mechanisms operating during eruptions. The surface descriptor variables like the number of quadtree blocks (nQT), the mean block size (mQT), the standard deviation of block sizes (sQT) and the surface descriptors derived from gradient analysis seem to be suitable for quantifying the structural changes of the ash surface due to variable explosion conditions. These parameters are presented in volcanology as distinctive key parameters for different eruption types. This may enrich our capabilities for effective prediction for the basis of planning to overcome the impending danger of eruptions.

Keywords: Nemrut; Volcanic ash; Hydrovolcanism; Quadtree decomposition; Gradient analysis

1. Introduction

1.1. Mount Nemrut

Mount Nemrut, an active stratovolcano in eastern Turkey, is a major danger for its vicinity. The volcano exhibits a summit caldera having a surface area of 8.5 km × 7 km. The eastern half of the caldera is filled by pyroclastic deposits related to maar-like explosion craters, lava domes and flows. The western half is filled by a freshwater lake covering a surface area of 5.3 km × 3 km and a small lake with hot springs. The fumarole activity is also present over a dome situated at the northern part of the caldera (Aydar et al., 2003). On the post-caldera stage of the volcano, related to the alternating...
mass ratio of interacting water and magma, sub-
plinian dispersal of pumice and air falls, base surge
deposits with dune and anti-dune structures, cross-
beddings, bread-crust bombs are observed.

1.2. Volcanic ash formation

Volcanic ashes are the particles with average
diameters $<2\text{ mm}$ those produced during volcanic
eruptions by mechanical fragmentation of magma
and/or country rock. There are three main mechan-
isms of volcanic ash formation: (1) the release of
gases due to decompression within the magma
ascending to the surface (magmatic eruptions),
(2) chilling and explosive fragmentation of magma
during contact with ground and surface water or
ice and snow (phreatomagmatic eruptions), and
(3) the comminution and ejection of particles from
vent walls or crater debris during eruptions of steam
and hot water (phreatic eruptions). Volcanic ash can
be produced by one or more of these mechanisms
(Heiken and Wohletz, 1985).

The term phreatomagmatic was introduced by
Stearns and MacDonald (1946) in reference to
explosions resulting from the conversion of ground-
water to steam by ascending magma. A phreato-
magmatic explosion refers to natural phenomena
produced by the interaction of magma or magmatic
heat with an external source of water, such as
surface body or an aquifer (MacDonald, 1972;
Sheridan and Wohletz, 1981). The products are
water, steam, juvenile clasts and brecciated country-
rocks (accessory and/or accidental xenoliths).

Accessory particles are fragmented co-magmatic
volcanic rocks from previous eruptions of the same
volcano. Accidental fragments are derived from the
subvolcanic basement and therefore may be of any
composition (Fisher and Schminke, 1984). Phreato-
magmatic deposits are rich in xenoliths indicating
the fragmentation of country rock with high
energies due to abundant water (vapour).

Volcanic ash deposits produced during these
eruptions are unique and their characteristics may
be used to interpret eruptive mechanisms. The
phreatomagmatic deposits contain grains that have
been significantly affected by a variety of processes
related to their formation, transport and alteration.
The common shapes of glass pyroclasts can be
ascribed to varying energies and modes of contact of
water with magma, including blocky-equant, moss-
like, plate-like and drop or spherical (Wohletz,
1983). Considering the explosive mechanisms and
the presence of such glass shapes show that
phreatomagmatic ash is formed by thermal con-
traction and shattering of glass which inhibits
vesiculation. The very drastic increase in viscosity
and the increase in solubility due to the decrease
in temperature prevent volatiles from exsolution
(Fisher and Schminke, 1984). The widely varying
clast vesicularities reflect complex variations in the
relative timing of vesiculation and water-induced
fragmentation. Magma–water interaction at an
early stage greatly reduces the vesicularity indices
(<=40%) and broadens the ranges (as high as 80%),
whereas late-stage interaction has only a minor
effect on the index and broadens the range to a
limited extent (Houghton and Wilson, 1989).

Deposits from phreatomagmatic eruptions are
characteristically fine-grained, although coarse-
grain lapilli- and tuff-breccias are common in
some deposits (Fisher and Schminke, 1984). Walker
(1973) shows that the median diameters is less than
1 mm in about 75% of the samples from phrea-
tomagmatic explosions in Azores and Iceland. In any
fragmentation mechanism the generated particles
sizes reflect the kinetic energy available (i.e., the
fragmentation energy density). Consequently, fine
ash provides information on fragmentation me-
chanisms that are the most energetic and related to
the highest explosive energy release (Zimanowski
et al., 2002). With increasing water interaction,
phreatomagmatism increases in explosivity. The
abundance of fine ash (<63 µm) increases from 5
to over 30% as water interaction reaches an
explosive maximum (Wohletz, 1983).

An important consideration is that both magmatic
and phreatomagmatic fragmentation mechanisms
may operate during an eruption. This situation was
illustrated by Self and Sparks (1978) for phreatopli-
nian silicic eruptions in which magma is initially
disrupted by exsolution and expansion of magmatic
volatiles, producing relatively coarse-grained pyro-
clasts. Further fragmentation (fine-grained pyro-
clasts) is caused by explosive interaction with
water. Theoretical consideration of experimental
fragmentation mechanisms suggests that stress waves
produced by high-pressure, vaporization of water at
the magma/water interface may, in part, induce
vesiculation in the melt (Heiken and Wohletz, 1985).

1.3. Classification of volcanic ash

Scanning electron microscopy (SEM) provides a
method for classifying volcanic ash based upon
surface morphology and texture (Wohletz and Krinsley, 1982). Heiken (1972, 1974), Wohletz (1983) and Heiken and Wohletz (1985) presented the most extensive SEM studies of pyroclast shapes and found a marked difference in grain morphology between magmatic and phreatomagmatic ashes. While some forms of glassy particles refer to phreatomagmatic or magmatic fragmentation, the lack of clear “key” structures prevents the classification (Dellino and La Volpe, 1996). The success in the discrimination depends on the experience of microscopist (Sheridan and Marshall, 1983). Thus the analysis of the volcanic clast shape remained largely qualitative (Marshall, 1987).

Dellino and La Volpe (1996) introduced new methods using particle outline parameters such as elongation, roundness, compactness and rectangularity to define the particle forms from Monte Pilato-Rocche Rosse. The outline parameters are influenced by transportation mechanisms (Dellino and La Volpe, 1996) and the effects of transportation abrasion may be misinterpreted as fragmentation features or vice versa.

1.4. Texture characterization

Several texture descriptors have been developed to characterize the detailed surface structure of, e.g. aluminium (Lee et al., 1998), aggregate (Rao et al., 2003), wear particles (Stachowiak, 1998) and paper surfaces (Chinga et al., 2003; Chinga, 2004). Fractal dimension, autocorrelation, gradient analysis, bandpass filtering, wavelet analysis, roughness statistics and quadtree decomposition have been applied to assess complex surface structures (Panozzo Heilbronner, 1992; Costa, 2000; Chinga et al., 2003; Chinga, 2005). In this respect, quadtree decomposition seems to be an easy, intuitive and powerful technique for characterizing the horizontal and vertical variation of surfaces (Chinga, 2005).

Hierarchical data structures are becoming increasingly important representation techniques in the domains of computer graphics, image processing, computational geometry, geographic information systems, and robotics. They are based on the principle of recursive decomposition. One such data structure is the quadtree (Samet, 1984). In the fields of image processing, computer graphics, and remote sensing two-dimensional point and region data are often indexed using quadtrees (Samet, 1990). Currently, quadtrees are used for point data, regions, curves, surfaces, and volumes. In this paper, the quadtree representation of data is concerned with the representation of region data. A region quadtree is a representation of a regular partitioning of space where regions are split recursively until there is a constant amount of information contained in them (Wang and Armstrong, 2003). Each quadtree block (also referred as a cell, or node) covers a portion of space that forms a hypercube in $d$-dimensions, usually with a side length that is a power of 2. Quadtree blocks may be further divided into $2^d$ sub-blocks of equal size; i.e., the sub-blocks of a block are obtained by halving the block along each coordinate axis, forming an adaptive grid (Fig. 1A). A quadtree may be considered as an extended $2^d$-ary tree, i.e., a tree in which every non-leaf node has $2^d$ children (Fig. 1B). A quadtree is thus a tree, where the branch structure is based on space coverage (Hjaltason and Samet, 1999).

Gradient analysis is also suitable for describing texture orientation. Similar methods have been used to detect the orientation of short-fibre composites (Gadala-Maria and Parsi, 1993) and actin fibres in cytoskeletal structures (Yoshigi et al., 2003). This may be valuable information for differentiating between textures having the same greylevel variation. The gradient analysis is based on Sobel operators as described by Gonzalez and Woods (1993) and implemented by Chinga et al. (2003).

This study introduces a new method for ash particle characterization based on a quadtree decomposition approach and gradient analysis. The approach is applied for assessing fragmentation mechanisms operating during eruptions. The calculated quadtree variables like the number of blocks

![Fig. 1. (A) Block decomposition; (B) tree structure of a simple quadtree, where leaf blocks are labeled with numbers and non-leaf blocks with letters (reproduced from Hjaltason and Samet, 1999).](image-url)
(nQT), the mean block size (mQT) and the standard deviation of block sizes (sQT), as well as surface descriptors derived from gradient analysis seem to be suitable for quantifying the structural changes of the ash surface due to variable explosion conditions. These parameters are presented in volcanology as distinctive key parameters for different eruption types.

2. Materials and methods

2.1. Sample description

Three samples denoted Nemrut1 (N1), Nemrut2 (N2) and Nemrut3 (N3) and indicating the changes in eruption styles were selected. Samples were taken from the very proximal location, the interior side of the caldera rim. Unvesiculated and rounded particles with hydration cracks are common in sample Nemrut1 which was collected from a base surge deposit. Few vesicles on Nemrut1 are filled with adhering dust. Particle morphologies of this sample exhibit the water effect. Sample Nemrut2 is highly vesiculated. The tubular vesicles are prevalent indicating the effects of a magmatic origin. Nemrut3 is also highly vesiculated, and exhibits tubular vesicles. It is not easy to separate the phreatoplinian samples Nemrut2 and Nemrut3 with naked eye. In the field, the arrangement of deposits from base to top is Nemrut3, Nemrut2 and Nemrut1 indicating the progressive increase in amount of water interacting with magma.

In addition, 160 samples were collected from the Nemrut Volcano (Turkey) for ash details determination. The samples from Nemrut show differences in bed structures, grain sizes, xenolith contents, density and vesiculation indicating the continuous changes in the eruption style (for details see Ersoy et al., in preparation). The grain size analysis includes drying, sieving and weighting of the different grain-size classes in phi scale. Percentage of tephra finer than 1 mm and median diameter (Md) were used to show the finer grain sizes related to high explosion energies due to abundant water. Particles of the 2–4 and 4–8 mm size classes were hand-picked under a binocular stereoscope for particle analysis. The different components were weighed and the weight percentage was calculated. The components are juvenile vesicular grains, unvesicular juvenile clasts and brecciated country-rocks (xenoliths). The dense rock equivalent (DRE) density has been determined on non-vesicular, dense grains, while the average elst density is that of the most vesiculated fragments. The density of juvenile fragments was measured with a pycnometer after coating fragments with a silicon-based aerosol which has negligible mass. About 10 measurements per sample were carried out in the 4-8 mm grain classes. The mean values were then considered. The vesicularity index (V%) was calculated using the method of Houghton and Wilson (1989). The results for three samples N1, N2 and N3 are given in Fig. 2. The percentages of material finer than 1 mm in samples show the decreasing grain size through the explosion produced the last sample (N1) with abundant water interacted with magma. The decreasing median diameters also point the increasing water interaction through the eruption. The increasing xenolith contents through the last sample (N1) also exhibits increasing fragmentation of country rocks with increasing energies due to the abundant water (vapour). The increasing densities and decreasing vesicularities of particles demonstrate the increasing role of external water versus magmatic volatiles in driving explosive eruption.

2.2. Sample preparation and image acquisition

The samples from the three eruption types were washed to remove any organic, loosely adhered and cementing material. Depending upon the freshness of the grains, washing included soaking in hot, dilute HCl and acetone or cleaning in acetone using ultrasound for not more than 4 min to preserve grain edges (Heiken and Wohletz, 1985). The samples were mounted on stainless-steel stubs using double stick tape and coated with carbon in order to counteract grain surface charging while scanning with the electron beam.

A CAMECA SU-30 operating at secondary electron mode with 17 KeV was used at Hacettepe University (Turkey) to take the whole grain and detailed surface photographs. The grain size interval of 250–355 μm was selected for comparing the textures with other studies (Wohletz, 1983; Heiken and Wohletz, 1985). Ten scanning electron images were acquired from each sample.

2.3. Image processing and analysis

Image processing and analysis of the secondary electron images (SEI) were performed using the ImageJ program (Rasband, 2004). The SurfCharJ plugin (Chinga et al., 2003) was used for surface
assessment and gradient analysis. The SurfCharJ plugin describes surface representations by calculating surface statistics like the standard deviation, the skewness, the kurtosis, mean greylevel (mGL) and standard deviation of greylevel values (sGL). The statistics were calculated for all the images. The standard deviation is given by

\[
\text{Standard deviation} = \sqrt{\frac{1}{wh} \sum_{x=1}^{w} \sum_{y=1}^{h} (z - z_{xy})^2},
\]

(1)

where \(w\) and \(h\) are the image dimensions, \(z\) the mean greylevel and \(z_{xy}\) local greylevel at local position \(x,y\). For details about the surface descriptors yielded by the SurfCharJ plugin see Chinga et al. (2003).

A gradient analysis based on Sobel operators was performed. The computation of the gradient of an image is based on obtaining the partial derivatives at every pixel. Derivatives may be implemented in several ways, however, the Sobel operators have the advantage of providing both differencing and a smoothing effect (Gonzalez and Woods, 1993). This smoothing effect of Sobel operators is particularly attractive due to the noise enhancing effect of derivatives. Derivatives based on Sobel operator masks are

\[
G_x = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)
\]

(2)

and

\[
G_y = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7),
\]

(3)

where the \(z\)’s represent the greylevels overlapped by the \(3 \times 3\) mask at any location in an image. The numbering of the \(z\)-values corresponds to the sequence from left to right, top to bottom in a \(3 \times 3\) mask. The direction at the location of the

Fig. 2. Determination of volcanic ash details. (A) Percentage of tephra finer than 1 mm; (B) xenolith ratio; (C) density; (D) vesicularity index.
centre of the masks is given by

\[ \alpha(x, y) = \tan^{-1}\left( \frac{G_y}{G_x} \right), \]

(4)

where the angle is measured with respect to the \( x \)-axis (for details see Gonzalez and Woods, 1993).

The images, filtered with Sobel operators, yield azimuthal images with gradients having values in radians, which are converted to angles between \(-180^\circ\) and \(180^\circ\) relative to the \( x \)-axis (Fig. 3B). The frequency of the gradients is plotted in polar coordinates to form a polar plot indicating the preferred orientation of the structure.

The polar plot was analysed with the Shape descriptor plugin (available at http://home.online.no/~gary.c) for assessing the shape of the generated plot. Different shape descriptors like the aspect ratio, compactness, roundness and form factor were calculated according to Russ (1999). The form factor seems suitable for describing the polar plot shape (Eq. (5)).

\[
\text{Form factor} = \frac{4\pi A}{P^2},
\]

(5)

where \( A \) represented the area and \( P \) the perimeter of a given polar plot (Fig. 3C). A circular polar plot has a form factor equal to 1 and indicates a structure having gradients oriented in all directions. Lower form factor values indicate flattened polar plots and a higher degree of structure orientation in specific directions as indicating in Fig. 3C.

A quadtree decomposition routine interfaced to the ImageJ program was used for texture characterization (Chinga, 2005). The quadtree decomposition was performed by assessing the local greylevel standard deviation. A greylevel standard deviation (sGL) of 25 was used for the decomposition. If the image has a sGL value of 25, the image is divided into four sub-images or blocks. Each sub-image is evaluated again using the same criteria. Each sub-image having a sGL value larger than 25 is decomposed into four new sub-images. This is done iteratively until the local area (sub-image) has a sGL value lower than the given threshold. The variables yielded by the current decomposition are the number of blocks (nQT), the mean block size (mQT) and the standard deviation of block sizes (sQT).

SPSS (SPSS Inc, Release 9.0) was used for statistical analysis.

3. Results

The percentage of tephra finer than 1 mm, median diameters, xenolith ratios, density and vesicularity index show the increasing amount of water interacting with magma (Fig. 2). In addition to confirming the transition to a wetter explosion, the obtained results exemplify the necessity of suitable parameters for discriminating between different explosion mechanisms.

Three quadtree decomposition, two greylevel parameters and seven shape descriptors were calculated on images and polar plots of images. An analysis of variance (ANOVA) was performed on the potential surface descriptors for verifying their suitability for differentiating among the samples. A variable is accepted when the variance between groups (samples) is significantly larger than

Fig. 3. Structure orientation analysis. (A) Original greylevel image; (B) azimuthal image; (C) polar plot based on frequency of gradients. Bar in \( A = 100\mu m \).
the variances within the groups (replicates). The ANOVA tests for the accepted variables are given in Figs. 4–6. The greylevel standard deviation (sGL), the form factor (FF) and the number of quadtree blocks (nQT) seem suitable for differentiating between samples, having $p$-values well below 0.05 with a 95% confidence interval (CI).

Among all the evaluated surface texture descriptors, the greylevel standard deviation seems to give the best differentiation between the samples. However, this parameter alone is insufficient to describe the structure in detail. The greylevel and greylevel variation may vary significantly depending on the settings used for image acquisition. Besides, two different structures may have the same greylevel variation, but different texture. This is exemplified in Fig. 7. A gradient analysis revealed significant differences between the structures (Fig. 8). Fig. 7A has a texture with clear orientation compared to Fig 7B.

Though both images have the same global sGL, there are also clear differences with respect to the local greylevel standard deviation. This is exemplified in Fig. 9 where Fig. 9B has larger areas with lower greylevel variation, thus having larger and fewer blocks after the corresponding quadtree decomposition.

All the presented texture descriptors (sGL, nQT and FF) seem to model the transition from a drier explosion to a wetter explosion. In addition, a data reduction method, R-mode factor analysis was performed on the three variables. The term factor analysis was first introduced by Thurstone, 1931.

![Fig. 4. ANOVA of greylevel standard deviation of (sGL) variable. Samples Nemrut1 (N1), Nemrut2 (N2) and Nemrut3 (N3) are included in analysis. Mean values are given with corresponding 95% CI.](image)

![Fig. 5. ANOVA of form factor (FF) variable. Samples Nemrut1 (N1), Nemrut2 (N2) and Nemrut3 (N3) are included in analysis. Mean values are given with corresponding 95% CI.](image)

![Fig. 6. ANOVA of number of quadtree block sizes (nQT) variable. Samples Nemrut1 (N1), Nemrut2 (N2) and Nemrut3 (N3) are included in analysis. Mean values are given with corresponding 95% CI.](image)

![Fig. 7. Two images having same greylevel standard deviation, i.e., 36. (A) Image from N2 sample showing a clear texture orientation; (B) image from N3 sample. Bar = 100μm.](image)
The main applications of factor analytic techniques are: (1) to reduce the number of variables and (2) to detect structure in the relationships between variables, that is to classify variables. Therefore, factor analysis is applied as a data reduction or structure detection method. A hands-on how-to approach about factor analysis can be found in Stevens (1986). The utility of factor analysis is plotting the singular samples on a factor diagram as factor scores [Fr]. The numbers of extracted factors, 2 were determined by the scree test. The scree test is a graphical method first proposed by Cattell (1966). Cattell (1966) suggests finding place where smooth decreases of eigenvalues appears to level off to the right of the plot. To the right of this point, presumably, one finds only “factorial scree”. “Scree” is the geological term referring to the debris which collects on the lower part of a rocky slope. According to this criterion, we retain 2 factors in our study (Fig. 10). The discriminating diagram is generated by using the factors as axes and the surface descriptor values as data points. In this case two factors could explain the 98% of the variance. The discriminating diagram including the three proposed variables (sGL, nQT and FF) is depicted in Fig. 10. For comparison, the particle outline parameters such as elongation, roundness, compactness and rectangularity used in Dellino and La Volpe (1996) were calculated on Nemrut samples. A discriminating diagram based on the particle outline parameters is depicted in Fig. 11. The different samples overlapped on the diagram, thus indicating the poor suitability of shape parameters for discriminating between different ash samples.

4. Discussion and conclusion

Volcanic ash particles from different fragmentation mechanisms have different surface textures and morphologies (Wohletz, 1983; Heiken and Wohletz, 1985). The success in the discrimination of volcanic ashes from SEM images depends on the experience of microscopist (Sheridan and Marshall, 1983). Thus the analysis of the volcanic clast shape remained largely qualitative (Marshall, 1987). Volcanologists have a beneficial book with huge data about volcanic ash by the agency of Heiken and Wohletz (1985). The qualitative data of volcanic ash needs to be expressed in quantitative ways. This provides the use of supplementary methods, e.g.
statistical analysis, artificial intelligence and study on high dimensional data.

Simple and well-defined surface descriptors have been presented in this study. Parameters derived from a quadtree decomposition approach seem to be suitable for describing ash texture. Complementary information is obtained by performing a gradient analysis. The proposed image processing and analysis is simple to implement and requires little subjective intervention.

Although, the common shapes of glass pyroclasts in phreatomagmatic explosions such as blocky-equant, moss-like, plate-like and drop or spherical may be used as “key” structures, they are uncommon, indefinable or absent in some products related to the varying energies, modes of contact of water and chemistry of magma. Multicondition-driven mechanisms may produce pyroclastic deposits varying in fundamental properties such as dispersal, grain size, vesicularity and morphology of juvenile clasts, and the abundance of lithic or “wall rock” ejecta (xenoliths).

The products under the influence of modifying conditions can be discriminated from each other by using the properties mentioned above. Among the criteria used to distinguish the products of “dry” magmatic eruptions from “wet” phreatomagmatic eruptions, the vesicularity of the juvenile clasts is generally considered to be high in the former and lower in the latter case (Walker and Croasdale,
1972; Houghton and Wilson, 1989). Even though it is necessary to take all fundamental properties into consideration in such variable mechanisms, the quadtree decomposition variables as well as surface descriptors derived from gradient analysis, which may be directly related to vesicularity, clustered the ash particles between two end member mechanisms.

The most effective and most hazardous volcanic mechanism of conversion of thermal into kinetic energy is by phreatomagmatic explosion (Lorenz et al., 1991; Wohletz, 1986; Wohletz and Sheridan, 1983; Wohletz and Brown, 1995; Zimanovski et al., 1997). The fluctuations in the vesicularity of ash particles may permit the anticipation of volcanic hazards. Textural analysis performed during the course of eruption may enable the prediction of some important changes in the eruptive style (Gourgaud et al., 2000). Complementary details may be obtained by assessing the ash surface topography, thus yielding valuable information about, e.g. vesicularity of the ash particles. This may enrich our capabilities for effective discrimination between magmatic and phreatomagmatic pyroclastics. The activities of volcanoes in heavily populated areas need to be monitored by various methods to detect precursory signs to enable scientists to issue advisories and warnings to the public and authorities in the area. This may also enrich our capabilities for effective prediction for the basis of planning to overcome the impending danger of eruptions.

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