Analysis of Thermal Video for Coarse to Fine Particle Tracking in Volcanic Explosion Plumes

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Abstract. This paper presents two algorithms for feature extraction and segmentation. The first algorithm is applied to detect tens of thousands of ballistic targets moving at high velocities (100's m/s) and with different sizes, velocities, shapes and directions. Upon detection, we compute statistics for each of these parameters for each particle, without any assumption or a-priori information. The second algorithm was developed to detect a slow moving convective cloud. The challenge was to follow the evolution of the cloud contours which comprised a heterogeneous element in front of a homogeneous, but moving (trees in wind), background. These algorithms were applied to images acquired with thermal cameras with different settings (frame rate, frame size, focal length, instantaneous field of view). A case study is presented using images of volcanic and made-man explosive events.

Keywords: Segmentation · Feature extraction · Contours · Thermal imagery

Introduction

The first high-temporal-resolution (operating at 20 Hz) ground-based infrared imaging system, was produced in 1965. However, the first hand-held system came with the introduction of high-spatial resolution focal plane arrays in 1993, with the first uncooled micro-bolometer-based system being produced in 1997. These developments, coupled with advances in high-speed digital electronics that allowed imagery to be stored on small memory disks “revolutionized the commercialization of thermal imaging systems” [1]. From that point onwards, infrared imaging science expanded rapidly in many domains [2]. Thermal imaging cameras (TIC) produce a thermal image of a scene that provides information regarding both its radiative and dynamic properties, a capability which makes TIC useful for a multitude of hot spot tracking roles.

Infrared Search and Track (IRST) systems were first developed for air defence applications [3], as well as for military applications. Today, they are also used in civil applications, such as surveillance on land, at sea and in the air and to provide warning of intruder ingress [4], as well as to survey areas where structural failure and disasters may occur. Thermal emission of gears operating on tanks or helicopters can, for example, be used to detect, track and lock-on to the target, so that many automatic target recognition (ATR) algorithms have been proposed to this end [5]. These algorithms segment and recognize vehicles, ships and aircraft [6]. TIC civilian applications include fire control [7], monitoring of buildings [2], medicine [8], computer-aided diagnosis systems [9] and volcanology [10].

One of the first field-based thermal measurement campaigns at an active volcano was completed by Thomas A. Jaggar [11,12]. He illustrated the benefits of remote thermal measurements against the common contact measurements, describing problems associated with contact-based measurement which included equipment and personnel safety as well as the limited measurement time available for a contact measurement imposed by the radiated heat from a lava lake. The first attempt to run a radiometer continuously at a volcanic target was completed for a persistently degassing vent by Tazieff [13] and during an explosive volcanic eruption by Shimozuru [14]. Between 1965 and the end of 2007, at least 60 studies reported results obtained using ground-based broad-band radiometers for explosions, fumaroles and geothermally heated surfaces as well as lava flow, lakes and domes [10]. Applications to volcanological science by thermal cameras were clustered in five main groups by Spampinato [15], these being studies of hydrothermal areas and fumarole fields; lava bodies; explosive activity and volcanic plumes; pyroclastic flow deposits; fracturing and cracking. The most popular of these applications has been analysis of explosive activity, which accounted for 48 % of the studies published between 2001 and 2011. In fact, some of the first publications involving the application of thermal camera data in the domain of volcanology focused on the dynamics of explosive eruption plumes [16]. The key advance in generating this popularity in volcanic studies has been the ability to collect thermal video with spatial resolutions of a few centimeters and sampling frequencies of up to 120 Hz, with the operator being free to choose and modify the dynamic range, sampling rate, field of view, and targeted area, as well as acquisition start and stop times.

Here, we thus focus on the application of thermal video data to explosive emissions where we aim to segment two major components of an explosive volcanic emission (plume) using the thermal data. First, we focus on all coarse particles as they exit the vent to gather parameters such as size, shape, velocity and mass for the solid (particulate) fraction of the plume, this being the contribution of particles with a diameter between 1 cm and 5 cm (lapilli-size) and between 6.5 cm to 35 cm (bombs-sized). We next analyze the plume of gas and fine particles whose ascent will be buoyancy driven [17] and which can rise to over 25 000 meters above the vent.

1 Particle Study (cm-sized analysis)

1.1 Methodology

The thermal camera used in this study was a forward looking infrared (FLIR) FLIR Systems SC655 equipped with a $3.6\times$ magnification lens and recording at 200 frames per second. The focal length was 88.9 mm and the IFOV was 0.19 mrad. We note that our frames are usually 600×480 pixels in size, but this is automatically truncated to allow recording at rates greater than 30 Hz. For example, at 200 Hz, the image size is 600×120 pixels. This resizing is automatically performed by the acquisition software and the resized frame is centered on the same pixel as the full frame and the spatial resolution does not change. The pixel dimension (L_p) will depend on the detector instantaneous field of view (IFOV). This is defined by a cone opening at angle β_{IFOV} and the distance to the target (D), so that the pixel diameter is given (for a paraxial approximation defined for a small IFOV), by $L_p = 2[D\tan(\beta_{IFOV}/2)] = D \times \beta_{IFOV}$.

Given the large number of particles involved in a volcanic explosion and the quantity of data recorded by the thermal camera (two hundred 640×120 pixel images per second = 150 kB of data every second or 1.8 GB per minute), we opted for a simple, yet-effective algorithm to extract particle parameters. A first step is to remove the static objects of the image. This is the static background, i.e. a set of components defined using the image prior to the event. The static background can usually be removed by pre-processing approaches [18]. Given the time of the event onset ($t = 0$), the easiest way to remove the static background is to consider the difference between the current frame I_t and a reference frame acquired before the event, termed the “background image” ($I_{t<0}$ or I_{Ref}). Now, we can detect the position of each particles in each image by subtracting the previous frame I_{t-1} from the current frame I_t . However, all moving elements are detected by this process, including slow targets we do not want to detect (e.g., birds, meteorological clouds). This is termed the “dynamic background”. Finally, we removed both the static and the dynamic background by generating a first derivative image at time t (T_t):

$$T_t = I_t - \frac{\alpha I_{t-1} + \gamma I_{Ref}}{\alpha + \gamma} \quad \forall t \in \{1, n\} \quad (1)$$

where α and γ are weights derived empirically and which change according to the predominance of the static versus dynamic background. After this step only particles and a low intensity hint of the background persist. Because we only want to detect components among the brightest features, we process $F_t = T_t \cdot \mathbf{1}_{\{I_t - I_0 \geq th\}}$ using a New White Top-Hat transform [19]:

$$MNWTH(F_t) = F_t - \min(((F_t \oplus \Delta B) \ominus B_b), F_t) \quad (2)$$

where $\oplus$ is the binary dilation operator and $\ominus$ the binary erosion operator. Parameters ΔB and B_b are respectively an empty and a full square-shaped

structuring elements. We apply a 21 pixel diameter box with, following Bai and Zhou [19], a three-pixel wide perimeter for ΔB . That is, while pixels in the central 15-pixel-wide box have values of zero, those in the three-pixel-wide perimeter have values of one.

The second part of the algorithm tracks each particle through time. This allows us to compute the velocity of each particle, but also cleans up false detections which may have occurred during the segmentation process. We chose the maximum intensity pixel of the target as the initial position with subpixel accuracy obtained following Shindler et al. [20]. Now, $\omega_{i,t} = (x_{i,t}, y_{i,t})$ is the subpixel position of particle i at time t . We defined the velocity of the particle in the image plane from the pixel distance traveled by the particle between two consecutive frames (Δt):

$$U_{i,t} = \frac{\|\omega_{i,t+1} - \omega_{i,t}\|}{\Delta t} \quad (3)$$

The next position of particle i can now be estimated following several conditions (spatial, intensity, trajectory). We then estimated the velocity in meters per second based on the frame rate and assuming a planar projection. Thus, dimensions in pixel (X_{pix} , where X may be a velocity or the pixel width or height) are converted in millimeters (X_{mm}) by

$$X_{mm} = \frac{RD}{f \sin(90 - \phi)} X_{pix} \quad (4)$$

in which R is the spatial resolution of the camera, D is the distance and ϕ is the tilt angle of the camera. Here, we are not interested in trajectories, instead our aim is to compute particle parameters as soon as they exit the vent. Consequently, we calculated our parameters using the closest usable frame to the vent. We used the radius of the particle short axis r_S and long axis r_L to compute the characteristic width of the particle i from the average radius, $r = \frac{r_S + r_L}{2}$. Particle volume (V_i) is then computed assuming a prolate spheroid, so that $V_i = (4/3)\pi r_S^2 r_L$. Finally, given an appropriate density (ρ_i), particle volume can be converted to mass ($m_i = \rho_i V_i$). This algorithm was tested and validated on an artificial experiment [21], a summary of which is given here.

1.2 Natural Case

The algorithm was tested on videos containing high velocity particles imaged at Stromboli volcano (Aeolian Islands, Italy). In 2012, we completed eight hours of recording spread over four days spanning 27 September-5 October during which time we recorded 13 eruptions. In 2014, we recorded for eight hours on 17 and 18 May, capturing a further 18 events. We set up our high speed camera at Pizzo Sopra la Fossa, a natural platform which overlooks Stromboli's active craters from a distance of 280 m, with the camera being tilted downwards at an angle of -23 degrees. With this geometry, we can detect particles down to 5.5 cm. Emission durations ranged from 5 s to 50 s, with an average of 14 s. The number of particles detected during single events ranged from 610 to 5 320, with

Fig. 1. Particles detected (bottom, in red) from the original image (top). Particles on the sides are static deposit from a previous eruption.

an average of 2 685. A total of 83 220 particles were detected for all 31 eruptions (Fig. 1). The particle size distribution (Fig. 2, top) revealed that the majority of the particles (67 %) were between the detection lower limit, 5.5 cm, and 10 cm; with the mean particle width being 10 cm on which there was a standard deviation of 5.6 cm. In Fig. 3, we assessed particle shape in terms of a normalized shape index: $(r_L - r_S)/(r_L + r_S)$. Following this index, a perfectly oblate shape will have a value of $-1/3$, whereas a perfectly prolate shape will have a value of $+1/3$; a perfect sphere will have a value of 0. We found that only 17 % of our particles approximated a spherical shape. Of the remaining 83 %, 29 % were oblate and 54 % were prolate. The dominance of the prolate shape is consistent with particle deformation in the direction of motion. We used the density of samples, from lapilli to bomb sized particles as collected during sample-collection campaigns to Stromboli in 2008 [22,23], 2010 [24] and 2011 [25] to compute the mass of each particle and the total mass ejected during each eruption. Derivations for erupted masses ranged between 1 270 kg and 11 820 kg, with a mean of 4 585 kg. The particle mass distribution (Fig. 2, middle) revealed that most particles had a relatively low mass, with 46 310 (or 56 %) of all of detected particles having masses of less than 4 kg. This population accounted for 10 220 kg or 4.6 % of the total mass. However, the 2 524 particles greater than 25 cm (3 % of the total detected particles) accounted for 44 % of the total mass.

The velocity distribution (Fig. 2, bottom) had a mode between 20 m/s and 30 m/s, with an average velocity of 45 m/s on which the standard deviation was 36 m/s. Particle velocities at Stromboli are generally less than 100 m/s [26,27]. In our study, 91 % of all of particles measured had velocities of less than 100 m/s. However, 7 330 particles (8.8 %) had velocities greater than 100 m/s and up to 240 m/s. This approaches the higher velocities recently found for normal explosion at Stromboli by Taddeucci et al. [28], Delle Donne and Ripepe [29] and Harris et al. [30]. Finally, considering the large number of particles detected (83 220), the impact of outliers is vanishingly small. We concluded that our dataset is statistically robust. Full data sets and overview statistics are given in Bombrun et al. [31].

Fig. 2. Particle size (top), mass (middle) and velocity distribution (bottom). Curves represent the cumulative number of particles. The mass histogram also shows in light gray the impact of the heavy particles on the total mass.

Fig. 3. Particle shape distribution. Positive values represent particle with a prolate shape while negative values are particle with oblate shape.

2 Plume Study (meter-sized analysis)

2.1 Target

Our primary objective was to develop an operational algorithm capable of detecting a moving plume and parametrizing its dynamics through time. A volcanic plume is a mixture of particles, gases, and entrained atmospheric air [32]. Such volcanic plumes are slow moving targets which may be dispersed on both local and global scales so that frame rates of 1 Hz are more than adequate. Consequently we recorded using a FLIR Systems SC660 saving at 3 second intervals onto an internal memory card. The focal length was 38 mm and the IFOV was 0.65 mrad

The first step of the algorithm was to consider the differentiation ($D_{t,t-step}$) between the current frame (I_t) and the previous frame (I_{t-step}) to highlight the dynamic background. We applied a single level discrete 2-D wavelet transformation, using a Daubechies wavelet (db1), on the absolute value of $D_{t,t-1}$ to compute the approximation coefficient matrix. The approximation coefficients are the high-scale, low-frequency components thus they contain much less noise than the original image and enhance the contrast but are slightly more than half the size of the original image. We next performed a direct reconstruction from the 2-D wavelet coefficient to obtain a reconstructed approximation image. From the absolute value of the reconstructed image, we computed a single threshold for the image using Otsu's method [33] to obtain a partial mask of the plume. We cleaned this mask by applying a morphological opening transformation with a 1 pixel radius disk and removing detected elements of less than 5 pixels in area. We completed this mask by performing the same process with another differentiation, $D_{t,Ref}$, this being the difference between the current frame (I_t) and a reference frame recorded before the event (I_{Ref}). We summed the two masks to obtain the final differentiated mask. However, because the wavelet transformation produced an approximation image, in the next step, we performed a morphological reconstruction, i.e., we applied a repeated dilatation process to the mask until its contour fitted the original image, I_t . Each successive dilation was constrained to lie underneath I_t . We cleaned the final image by removing outliers to finally compute the plume exterior contour using a Canny edge detector.

2.2 Applications

We first tested the algorithm on thermal video for the ascent of a volcanic ash plume at Santiaguito volcano, Guatemala. This video was recorded in 2005 and the emission was 170 s (5 100 frames) in duration. The background was composed of a homogeneous sky with low-intensity meteorological clouds, with the ground contrasting well with the plume (Fig. 4(a)). A low-intensity lava flow was apparent on the left-hand side of the vent. Unfortunately the algorithm was too efficient in considering low contrast image elements so that some (moving) meteorological clouds were detected as a part of the plume. We thus removed

clouds on the basis of their being not pixel-connected to the plume. This was achieved by considering the largest component and improved the contrast by using wavelets on the differentiated image as a pre-processing step.

The second video was recorded at Stromboli volcano, Italy on May the 28, 2012. The camera was set up at Pizzo Sopra la Fossa and pointed at the North-East crater over a line of sight distance of 300 m so that the image covered a height of 94 m. Plume emission lasted 67 s (i.e. 2 000 frames). The background was a homogeneous sky and cold ground around the vent, although another vent to the left of the active vent produced unwanted detections (Fig. 4(b)). In addition, the distance between the camera and the vent was shorter than at Santiaguito, thus the impact of heat radiated by the crater was more problematic. During plume ascent, overturn convection thermally renewed the plume surface so as to continually bring hot spots to the surface of the plume to create a random intensity to the plume images, thus making intensity tracking difficult.

The third video was recorded at an experimental facility near Buffalo, USA. During June 2014, the University at Buffalo completed experiments that used small chemical explosive charges buried in layered aggregates to simulate the effects of subsurface hydrothermal and phreatomagmatic explosions [34]. At the same time, three more powerful blasts were performed. These released a plume of fine sand particles. The blast used to test our algorithm was that of Pad 5, Blast 4. The energy produced by the explosion was 2.30×10^6 J and the depth below the surface was 0.5 m. The camera was set up 74 m from the source so that the

Fig. 4. Performance of the plume segmentation algorithm applied to videos from Santiaguito volcano (a), Stromboli volcano (b), Buffalo (c) and Munich experiments (d)

field of view was 23 m height. The ambient background was composed of trees at ambient temperature, moving in the wind to create a moving background. The top of the video comprised sky that had a huge contrast with the trees. This video was the most difficult to process due to the numerous and contrasting features in the video (Fig. 4(c)).

The last video was recorded at an experimental facility near Munich, Germany, where the Ludwig-Maximilians University completed large-scale ash settling experiments in June 2014. Natural basaltic ash (0 – 500 μm) was released with different controlled volumetric flow rates in a shock tube system. The experiment used to test our algorithm was that of experiment #33. The sample came from Monte Rossi Scoria (Italy); it was water saturated, the sample porosity was 30 %, its volume was 29.44 cm^3 and the pressure of the decompression was 15 Mpa. The camera was set up horizontally at a distance of 4 m so that the field of view was 1.2 m height. The algorithm succeeded in performing plume detection despite the fact that the sample was colder than the background (Fig. 4(d)).

Conclusion

We present, here, new approaches to deal with segmentation and feature extraction in thermal video obtained for explosively-generated plumes. The first algorithm detects, tracks and parameterizes small dim, but relatively large (ballistic) targets in high-speed IR videos. Based on a mathematical morphology transformation hybridized with refinement by thresholding, this method allowed us to obtain a statistically robust database of 83 000 particles emitted during explosions at Stromboli volcano. Statistically, most of the particles have sizes between 5 and 15 μm , and the majority of individual particle masses are below 0.5 μg . The particle velocity distribution is positively skewed with a mode between 20 and 30 m/s. The second algorithm detect and track fine particles in plumes ascending under buoyancy. The detection method applied to this case is based on a background subtraction by Daubechies wavelet transformation with a refinement by image reconstruction. It was tested on several cases with different levels of difficulties. Even so, this algorithm proved to be robust enough to detect plumes despite of complex image background scenarios. These two algorithms are designed to provide necessary information to allow improved understanding and modeling of dynamics for all ejected components during volcanic explosions. Statistically robust databases for vent-leaving particle dynamics remain scarce.

The ability to measure the dynamics of volcanic emissions as they exit the vent and the computation of particle parameters, for all particle sizes - from fine (ash) to coarse (lapilli-bombs) - is an excellent way to understand the dynamics related to the fragmentation and particle emission processes that lead to the volcanic plume and cloud. In this regard, using algorithm output to compute plume parameters such as height, front velocity and spreading angle will be used to constrain models that describe the source geometry and height of volcanic jets.

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