ORDER FROM CHAOS: A QUANTITATIVE APPROACH TO IDENTIFYING SMALL CHAOS FEATURES ON EUROPA.
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Introduction: Chaos is an iconic surface feature on Europa. It is loosely defined as isolated patches with a hummocky surface, a clear disruption of older terrain, low albedo, and distinct reddish-brown material [1]. The locations of chaotic terrains on Europa have been reported in several studies [2-8], but most chaos mapping that includes smaller features (≤10 km) has been limited to the ~10% Europa's surface imaged at sufficient resolution to resolve the characteristic morphology of chaos. Although attempts have been made to construct a global map of chaos (e.g. [8]), differences in image resolution, viewing geometry, and lighting conditions make robust characterization challenging [6].

Chaos features are thought to be the direct result of heat transport within Europa's ice shell [9]. Though multiple heat transport models describing the formation of Europa's chaos exist, none fully explains all instances of chaos. Because chaotic terrain is generally redder than other terrains, perhaps due to the presence of salts on Europa's surface [10], it may be possible to use color data from *Galileo* to constrain the extent of chaos on Europa's surface even in low-resolution (≥ 1.5 km/pixel) images. Knowing the locations of chaos and the scales on which it occurs will help to constrain chaos formation models.

We present preliminary results of a new method to quantitatively discriminate between different types of microfeatures (≤ 100 km^2) on Europa, specifically between chaos and non-chaos terrains, to create a global map of chaos at small sizes. We begin by mapping features in higher-resolution (≤ 400 m/pixel) regional mapping images and identifying characteristics that can robustly discriminate between feature types. In particular, we assess the efficacy of darkness and color in identifying chaos on Europa.

Methods: All of the images used in this study derive from the Solid State Imager (SSI) camera on the *Galileo* mission to the Jupiter system [11]. The images used here are from the northern portion of the 15th flyby orbit of Europa (called E15). This mosaic is centered at 225° longitude, and covers an approximate total area of roughly 350,000 km^2.

Mapping. All small features of any morphology were mapped as standard polygons in ArcGIS. Features that could be identified as a specific type of morphology (chaos, spot, dome, or pit) were noted and categorized subjectively based on contextual clues in the actual images. Features that could not be attributed to one group were left unclassified. In total, ~85% of the mapped features were attributed to a certain feature class, with the remaining 15% unclassified. The microfeature population contained 184 chaos features, 10 spots, 174 domes, and 80 pits. For each of the 522 features, we recorded five characteristics: area (km^2), perimeter (km), maximum length (km), maximum width (km), and darkness (greyscale digital number divided by 255, the maximum value for the 8-bit SSI) [11]. Darkness is often correlated with redness [1, 10], enabling us to conduct a preliminary analysis before collecting color data for the microfeatures.

Statistical analysis. Using the data collected for each microfeature, we conducted a discriminant function analysis (DFA), which is primarily used to sort data points of unknown origin or morphology into two or more naturally occurring groups [12]. This test is similar to the multiple analysis of variance (MANOVA) test, but differs in that the DFA requires independent, continuous variables measured and reported for each data point [12].

A limit of the DFA is that it assumes the list of groups is complete, and will only sort data points into one of the predetermined groups; in this case, the groups are the four types of microfeatures identified in the E15-01 images. The DFA will then test in-group variances of each of the microfeature characteristics and compare them to the between-group variances. Data points that are not assigned to a group will be forced into the group to which they are most similar according to their individual characteristics. The DFA then plots both grouped and non-grouped data according to two functions with the highest eigenvalues. The plots and functions show the degree to which the groups differ with respect to the individual characteristics.

Area and perimeter did not follow normal distributions, a violation of one criterion of the DFA [12], so two ratios were substituted for these data instead. These ratios are: 1) the square root of the area divided by the perimeter, and 2) the maximum length divided by the perimeter. Both values give some sense of the irregularity in shape of each feature. Eccentricity was calculated as the maximum length divided by the maximum width. Each of these "morphometric" variables follows a roughly normal distribution.

We conducted two tests with slightly different weighting schemas. In the first analysis, the probability of any unclassified data point being sorted into any one group was equal for each group (25%), and in the second analysis that same probability was weighted based on the relative size of each group.

In order to determine how effectively the DFA sorted features, we conducted a cross-validation test, in which each classified data point is removed from its group and subsequently remapped according to the functions derived from all other data points. The test is considered successful if the data point is reclassified into its original group.

Results and Discussion:

Darkness variable excluded. The first analyses only included morphometric characteristics of the data (eccentricity, Ratio 1, and Ratio 2), and deliberately excluded any information regarding the darkness of the features. In the case where group classification probabilities were equal, cross-validation was successful in only 24.8% of cases. In the case where group classification probabilities were weighted, cross-validation improved to 40.5%. As shown in Figure 1, the four microfeature types overlap, making correct placement of unclassified features challenging.

Darkness variable included. The analyses were repeated, this time with darkness included as a sorting variable. In the case of equal group classification probability, 57.9% of cross-validated cases were successful. In the case of weighted group classification probability, 70.7% of cross-validated cases were successful. However, the success rate for sorting chaos features is 91.8%. In other words, while some feature types are not easily distinguishable, chaos features separate out from the other three types. These results are shown in Figure 2.

Conclusions: The goal of this project was to use a DFA to discriminate between chaos and non-chaos terrain on Europa's surface, with ultimate applications to the Europa Multiple Flyby Flagship mission objectives. In the cases where only the morphometric variables (the ratios and eccentricity) were included, the success of cross-validation was, at best, 40%. This is due to the fact that many of these microfeatures present as morphometrically similar, especially in terms of eccentricity, at the 200 m/pixel scale. When darkness is added as a sorting variable, the success of cross-validation increases to roughly 70% and is >90% for chaos features specifically. Because darkness and redness are correlated, we anticipate more robust sorting once color is included in the analysis.

Our next step involves mapping features in additional, well-imaged regions, measuring the redness of all features using color data taken by *Galileo*, and conducting additional DFAs to obtain the most robust criteria for identifying chaos. We will then attempt to map chaos features in lower resolution images of the same regions to determine the limits of our ability to reliably find chaos using this approach. Our ultimate goal is to create a global map of chaos features down to sizes of ~10km, which will provide important constraints on the formation mechanism of chaos.

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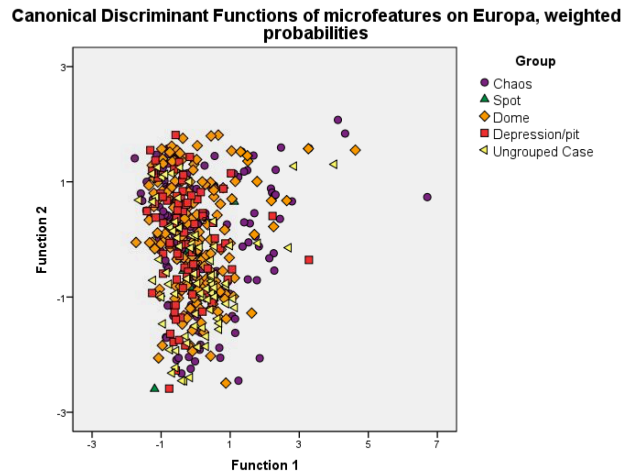

Figure 1: The DFA shows all groups overlapping when darkness is excluded as a sorting variable.

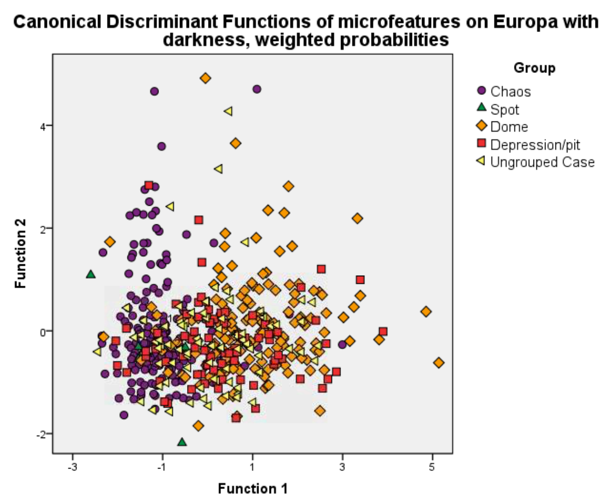

Figure 2: The DFA shows the chaos group separating from the other features when darkness is included as a sorting variable.