DISCRIMINATION OF SURFACE TEXTURES USING FRACTAL METHODS

JILL P. CARD*, J. M. HYDE*, AND T. GIVERSEN*
**Digital Equipment Corp., 77 Reed Rd., Hudson, MA 01749-2810*

ABSTRACT

This paper investigates the use of fractal metrics for discrimination of copper surface textures. Measurements of copper surfaces, using contacting profilometry, provided the raw data for the fractal analysis. The samples tested included copper foil samples and a copper lead frame, typical of those in use in plastic electronic packages. The fractal Hausdorf dimension and upper/lower ranges of fractal scale are analyzed by the coastline method and compared using Bonferroni multiple confidence limits. Metrics show significant differences between sample couplets, indicating significant precision in the fractal approach to adequately quantify surface texture qualities.

INTRODUCTION

Many techniques are used to measure surface roughness and to obtain a quantitative value descriptive of the properties of the surface. Contacting stylus profilometers output metrics such as average roughness, average peak height, and maximum peak to valley height difference. These quantities, though useful for some measurements, may not adequately differentiate among complex surface textures for which the distributions of peak heights and valleys differ, although the ranges and/or means do not. A more powerful metric, containing a more detailed description of the surface, is required.

A precise characterization of surface features is required for adhesion studies. Adhesion involves both mechanical and chemical contributions, which are interdependent. A rough surface does not necessarily imply poorer adhesion than a smooth surface although the latter has better wetting characteristics. In some cases, notably that of the adhesion of epoxy resin to copper, rougher surfaces can improve the adhesion strength[1]. That example is of particular interest due to the similarity to adhesion between epoxy-type molding compounds and copper lead frames in plastic electronic packaging.

Adhesion is a crucial factor in plastic packaging where delamination, or loss of adhesion, can lead to corrosion problems and device failures. It is important to optimize the adhesion between the lead frame and the molding compound. This paper looks at various copper foils, as prepared by suppliers for printed wiring boards, and at a copper alloy lead frame, representative of those used in plastic electronic packages.

The textures of various metal surface finishes have been recently successfully distinguished utilizing 2D or 3D fractal analytic techniques[2-7]. Fractal-based metrics capture texture properties, such as the ranges and frequency of self-similar surface peaks, not previously possible using traditional measures (e.g., average roughness and peak-to-valley metrics). This enables the use of metrics as predictors of physical texture-dependent phenomena such as fracture toughness[7], cleanability of metal surfaces[2], and silicon wafer surface quality[8]. The motivation for this study is to define a set of fractal-based metrics which are sufficiently accurate to capture the concept of surface texture in characterizing metal lead frame to plastic package adhesion.

The coastline method[9] of fractal dimension computation is used for all analyses presented here. Other profile and surface area based methods for determining the fractal dimension are well

Mat. Res. Soc. Symp. Proc. Vol. 367 ©1995 Materials Research Society

documented [10-13] and will be investigated for future comparison of fractal dimension estimation accuracy and precision.

The fractal descriptors of surface texture represent a parameter subset involved in the prediction of mechanical and/or chemical adhesion. Future work will incorporate the fractal metrics as well as other process parameters (e.g., temperature, pressure, viscosity) as inputs to an adhesion prediction neural network. A similar approach, using fractal characterization for feature extraction as an input into a neural network was proposed by Stubbendieck and Oldham[8] look for the detection of flaws in silicon wafers via neural network using a surface area fractal dimensioning technique for feature extraction.

EXPERIMENTAL PROCEDURE

The samples tested were four copper foils and a copper lead frame. The foil samples were: Sample 1, 1 ounce double treated; Sample 2, 9 micron foil with aluminum backing; Sample 3, 1/2 ounce JTCAM; Sample 4, 1 ounce JTCAM; and Sample 5, lead frame. The 1 ounce double treated foil was from Gould Electronics and was representative of the current standard foil preparation technology, also referred to as JTC. The 9 micron foil was from Foil Technology and was expected to have a smoother surface than JTC. The JTCAM foils were from Gould and represented a new process intended to produce foils with finer surface texture and higher surface area than the standard JTC treatment. The lead frame sample was representative of those used in plastic packaging.

The surfaces were measured using a Tencor P-1 profilometer with a 0.26 micron radius diamond stylus. Each scan was 0.5mm long and was comprised of 2561 height measurements. Five scans were made at five different locations on each sample. SEM images of the surfaces are shown in Figure 1. An example of the profilometer output is shown in Figure 2.

ANALYTIC METHOD

Fractal models have been successfully applied to describe a wide variety of natural surfaces and processes such as cloud formations, wave harmonics, coastline lengths, etc. Mandelbrot[9] proposed that the relationship between the measured length L and the ruler size N observed by Richardson[14]:

$$L(N) = L_0 N^{(1-D)} \qquad (1)$$

represents a fractal curve of Hausdorf dimension D, for $1 \leq D \leq 2$. The log $L(N)$ vs. log N plot, with measured slope (1-D), provides a means for estimating the fractal dimension of surfaces. Underwood and Banerji[15] proposed a modification of (1):

$$\log R_L(N) = \log C - (D-1)\log N \qquad (2)$$

where **C** is a constant and $\mathbf{R}_L$, the profile roughness parameter, is defined as the apparent profile length divided by its projected length.

The COASTFRAX[16] software used for this study employs the above "coastline" method of fractal dimension computation. The estimation of the fractal dimension D is determined by obtaining the most negative slope parameter fit (min $\{-(1-D)\}$) via regression analyses, the domain of each spanning a decade of ruler lengths and the collective domain of analyses spanning the total range of ruler lengths [6].

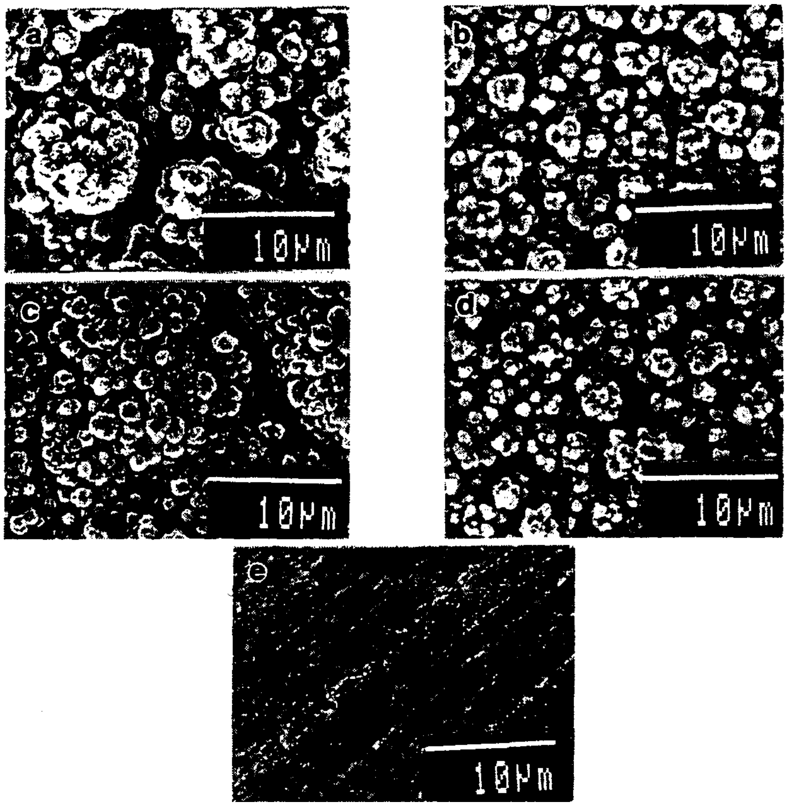

Figure 1. SEM micrographs of (a) Sample 1, (b) Sample 2, (c) Sample 3, (d) Sample 4 and (e) Sample 5, all at 2000X.

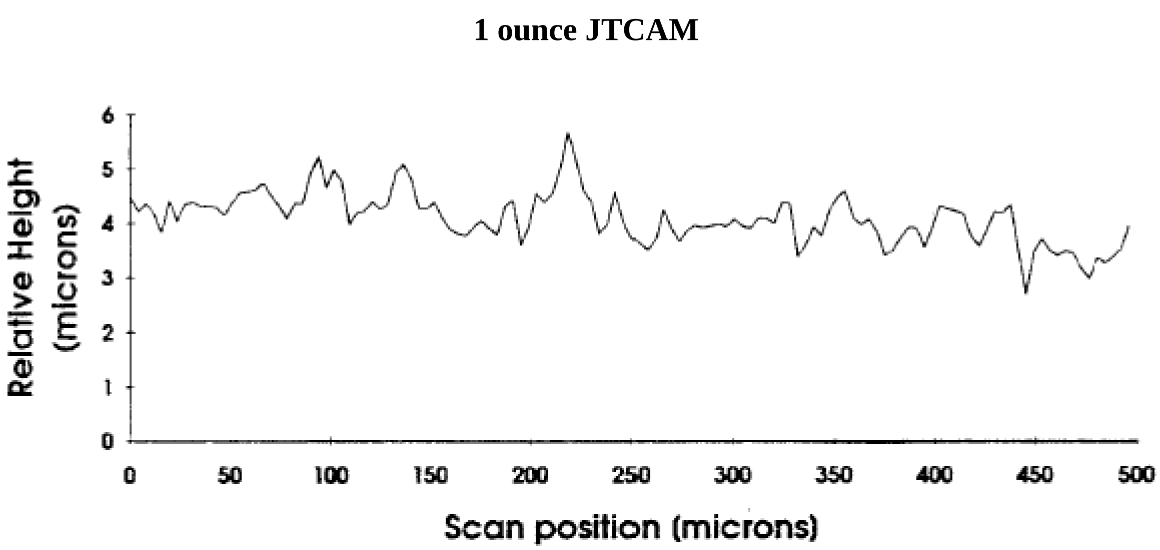

Figure 2: Example of a profilometer scan.

In addition to the slope parameter $-(D-1)$, lower and upper log ruler length crossover points were identified. These points represent the minimum and maximum ruler scale range over which the measured surface is fractal in nature. Below and above the minimum and maximum values, respectively, the slope of the log-log plot approaches zero. In instances where the minimum crossover point coincides with the size of the stylus diameter, the stylus is the limiting factor, rather than a change in the fractal nature of the surface. In this study, the stylus was .26 micron radius and was well below the anticipated lower crossover point. The COASTFRAX program computes the minimum (maximum) scale range crossover for a sample profile as the ruler scale value at which the profile roughness, $\mathbf{R}_L$, first decreases by 10% (90%).

RESULTS

All of the profile scans for the samples were analyzed using the coastline method described for obtaining the slope and the minimum and maximum crossover points bounding the scale region of fractal features. Figure 3 shows all 25 log R_L vs. log N plots. The sample slopes decrease with increasing sample surface roughness, as seen in Figure 1.

Table I lists the Bonferroni Confidence interval groupings for the five sample types for the three variables computed (slope, minimum crossover, and maximum crossover) for Type 1 error (α) = .05. The slope values for all 5 samples are significantly different from one another when compared by all possible pairs, with the exception of the Samples 2 and 4. The difference between these two means is .0019 and falls short of the .0029 delta required for significance at $\alpha = .05$. However, investigation of these two samples' dispersion in Fig. 1 suggests that a larger sample size would enable a more precise estimation of the fractal dimension and would result in discrimination between samples in the correct roughness order.

The Bonferroni simultaneous confidence intervals for all 2-sample comparisons for the minimum and maximum crossover metrics indicate that three distinct groups evolve, wherein the first group contains Samples 1 and 3, the second group contains Samples 2 and 4, and the third group contains Sample 5. As expected, the minimum and maximum fractal feature scale values for the coarser surfaces (Samples 1 and 3) show a significant shift toward a larger scale values than those of the very smooth lead frame.

CONCLUSION

Results of this preliminary investigation of texture discrimination of Cu surface foils via computation of fractal dimension and feature range from profilometric data proved to be promising. Of the 5 foil types investigated, all fractal dimension estimates significantly

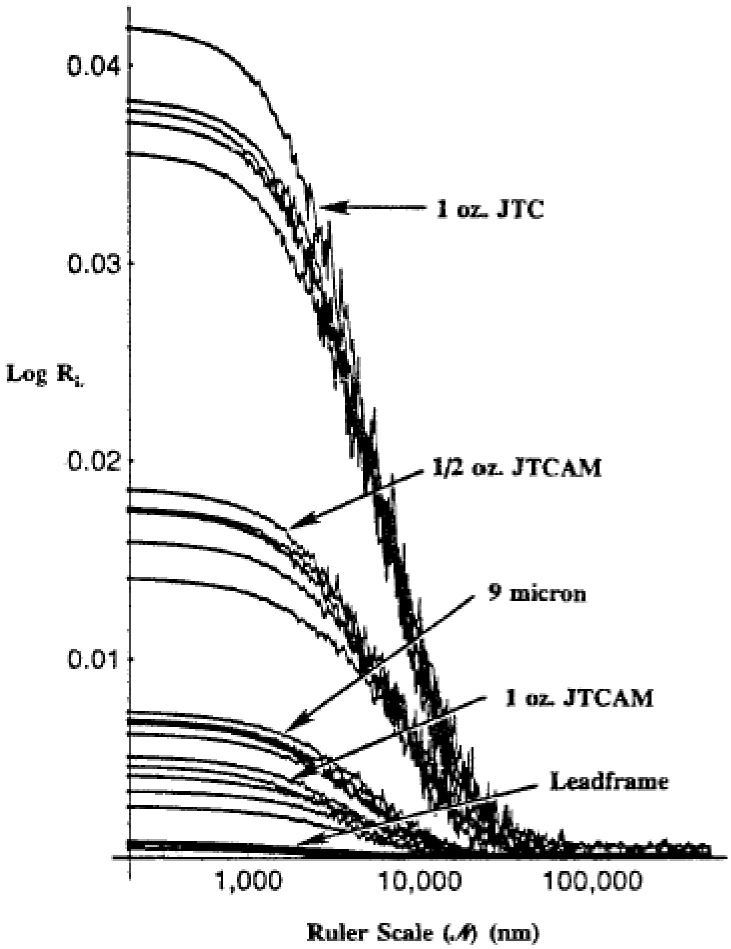

Figure 3. Plot of log (relative length) vs. log (ruler length) for all samples.

Table I: Bonferroni tests for multiple 2-sample mean comparisons. For dependent variables (slope, maximum scale crossover, and minimum scale crossover) a series of ten 2-sample mean difference comparisons are made, controlling overall Type I error = 0.05. Means with the same Bonferroni Group number are not significantly different.

Sample	Slope -(D –1)	Group	Min. Scale Crossover	Group	Max. Scale Crossover	Group
1	-.0312	A	1408.0	A	21400	A
3	-.0138	B	1496.0	A	21180	A
2	-.0054	C	1106.0	B	15140	B
4	-.0036	C	1036.0	B	12820	B
5	-.0005	D	521.6	C	6516	C
Min. Sign. Difference	.0029		156.77		4802.6	

discriminate between all samples, taken two at a time, with the exception of the 1 ounce JTCAM and 9 micron samples. For the latter two samples, the mean fractal dimensions were ordered rough vs. smooth, consistent with a visual assessment. The lack of statistical significance here is principally attributed to the small sample size used for the comparisons. Alternatively, another method of surface data collection, such as stereo scanning electron microscopy, may yield more precise measurements, thereby reducing the variance, and may be able to detect smaller mean differences than those obtained with the Tencor profilometer. In addition, a more precise algorithm for fractal dimension estimation, for either profiles or surfaces (e.g. box-counting, power spectrum, and the variation method) could also improve the discrimination among sample textures.

Use of the fractal dimension is anticipated to more thoroughly characterize textures and profiles than traditional surface measures such as peak-to-valley range and average roughness, due to the built-in mathematical aspects of fractal analysis reflecting the quantity, height, and slope of the peaks. Given the intention to use fractal metrics as input features to a neural network designed to predict the adhesion quality of metal lead frame materials to plastic packaging, it is important that the metric can discriminate at, or better than, the precision level of surface differences impacting adhesion. To this end, work will continue to investigate other fractal-based analyses of both profiles and surfaces (e.g. box-counting, power spectrum and the variation method for fractal dimension estimation) as well as other means of surface data collection.

REFERENCES

1. D.E.Packham, in Adhesion Aspects of Polymeric Coatings edited by K.Mittal (Plenum, NY, 1983). pp. 19 -41.
2. S. Chesters, H. Wang, G. Kasper, Solid State Technology, Jan. 1991, 73.
3. J.W. Martin and D.P. Bentz, J. Coatings Tech., **59** (745), 35-41 (1987).
4. A. Majumdar and C.L. Tien, Wear, **136**, 313 (1990).
5. C.A. Brown, P.D. Charles, W.A. Johnsen, S. Chesters, Wear, **161**, 61 (1993).
6. C.A. Brown and G. Savary, Wear, **141**, 211 (1991).
7. Y. Fahmy, J.C. Russ, C.C. Koch, J. Mater. Res., **6** (9), 1856-1861 (1991).
8. G.T. Stubbendieck and W.B. Oldham, IEEE Int. Joint Conf. on Neural Networks, **3**, 717-23(1992).
9. B.B. Mandelbrot, The Fractal Geometry of Nature, (W.H. Freeman and Co., New York, 1983), p. 25-57.
10. B. Dubuc, S.W. Zucker, C. Tricot, J.F. Quinlou, D. Wehbi, Proc. R. Soc. Lond. A, **425**, 113 (1989).
11. S. Peleg, J. Naor, R. Hartley, D Avnir, IEEE Trans. Pattern Anal. and Mach. Intell., **PAMI-6** (4), 518-523, (1984).
12. H. Fischer and J. Nittmann, CEC-Vienna Report No. 94-05, 1994.
13. B Dubuc, J.F. Quiniou, C. Roques-Carmes, C. Tricot, S.W. Zucker, Physical Rev. A, **39** (3), 1500-1512 (1989).
14. L.F. Richardson, General Systems Yearbook, **6**, 139 (1961).
15. E.E. Underwood and K. Banerji, Mater. Sci. and Eng., **80**, 1 (1986).
16. C.A. Brown, **Coastfrax** U.S. Patent pending, 1993.