Fracture-Mechanic Quantitative Matching of Evidence Fragment

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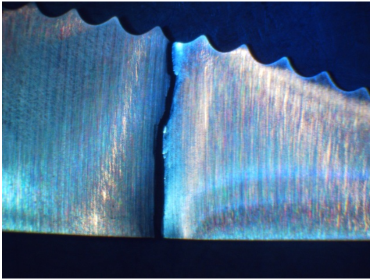
Outline of pre

- Introduction
- Collection and Imaging of Evidence Fragments
- Finding Patterns between Matches and Non-matches
- Statistical Tools for Matching and Confidence Assessment
- Illustration and Performance
- Concluding Remarks

Introduction to Problem

- Broken incomplete pieces, often found at crime scenes include
  - metal fragments
  - pieces of rubber, *e.g.* sole of suspects shoe
  - glass pieces (*e.g.* window or automobile glass)
  - plastic (objects or auto parts)
  - wood (bats or blocks)
- Reliably matching fragments, especially those found partly at crime scenes and partly elsewhere important
  - also want to numerically quantify confidence in decision
- Focus on metal fragments

Example: Matching Two Knife Fragment

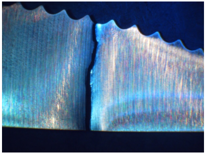


true match

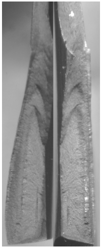
false match

- Consider the example of knife fragments, part of which has been found at a crime scene and the other part possibly found at a different location.
- Interest to determine whether two fragments match.
  - confidence in the probability of matching

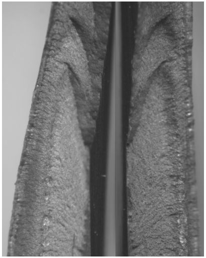
Matching Knife Fragment



no magnification



10x



20x magnification

- Traditional forensics practice visually compares fracture surfaces of materials to determine if two separate pieces of material can possibly belong to the same origin
  - physical characteristics of the fracture, such as shape, color, and other surface features
  - tactile pattern matching under comparative microscopy
- Confidence in decision not always numerically quantified.

Matching Knife Fragment

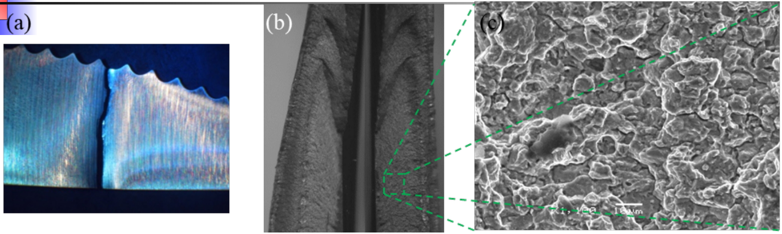


Figure: Association of forensic fragments. (A) Visual jigsaw match of the macroscopic crack trajectory. (B) Tactile pattern match with comparative microscopy. (C) SEM image of the microscopic details of the tortuous path of a crack through or around the microstructure's grains, showing the microscopic features of the fracture surface.

- Complex jagged trajectory of macro-crack through given forensic article can be used to recognize a "match".
  - use unique features of microstructure along fractured surfaces to determine match.
- Derive objective approach with quantified confidence.

Fundamental Premise of Phy Matching

- Basis for physical matching is assumption of indefinite number of matches all along the fracture surface.
  - contend that irregularities of fractured surfaces are unique
  - rough and irregular metallic fracture surfaces carry many details of metal microstructure as well as loading history.
    - exploit for forensic purposes.
- Randomly propagating crack will exhibit unique fracture surface topological details when observed from a global coordinate that does not recognize crack propagation direction.
  - uniqueness of these topological features mean that they can be used to individualize and distinguish the association of paired fracture surfaces.
- Hypothesis: microscopic features of the fracture surface possess unique attributes at some length scale that arise from the interaction of the propagating crack-tip process-zone and microstructure details.

Uniquene of Fracture Surface Co

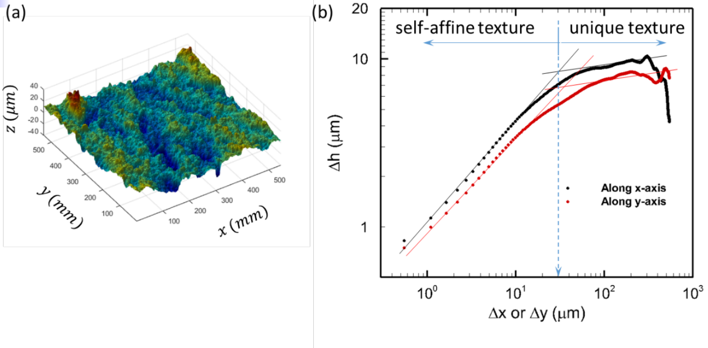
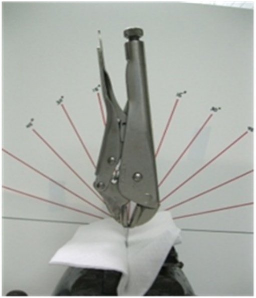


Figure: Fracture surface characteristics. (a) 3D surface topology rendering of fractured surface, showing a biased orientation of the low frequency texture of the fracture surface. (b) Height-height correlation variation with the size of the imaging window, showing the domain of the self-affine characteristics of the fracture surface, and its upper limit with saturation corresponding to long-range roughness ($> 100\mu m$)

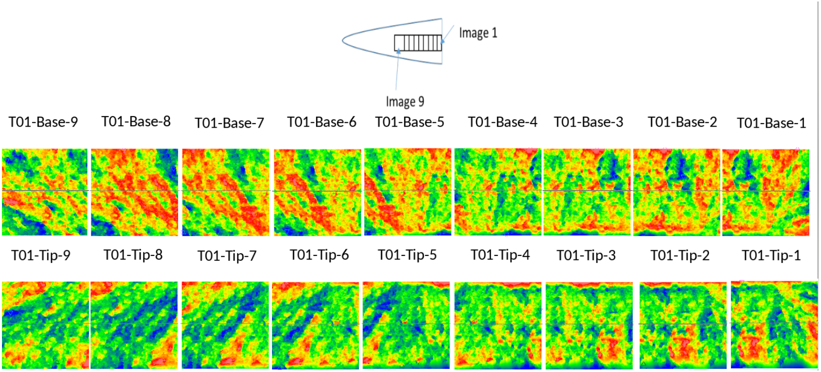


bending fixture

set of fractured knives

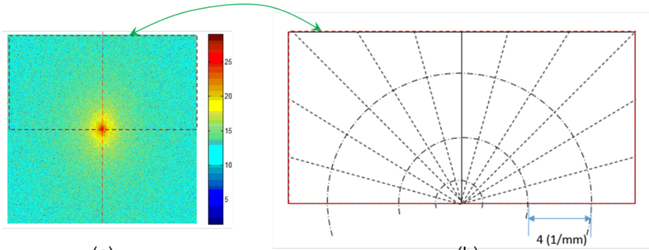
- Set of nine knives, each broken similarly with bending
- Obtain tip-base pairs for each sample
  - surface images by standard non-contact 3D optical interferometer (Zygo-NewView 6300)
  - samples provided both match and non-match specimens
- Data on second set of knives – *training* & *test set*

Imaging Setup



- Imaging with 75% overlap between adjacent surfaces.
- 2D FFT of each image – analysis in spectral domain

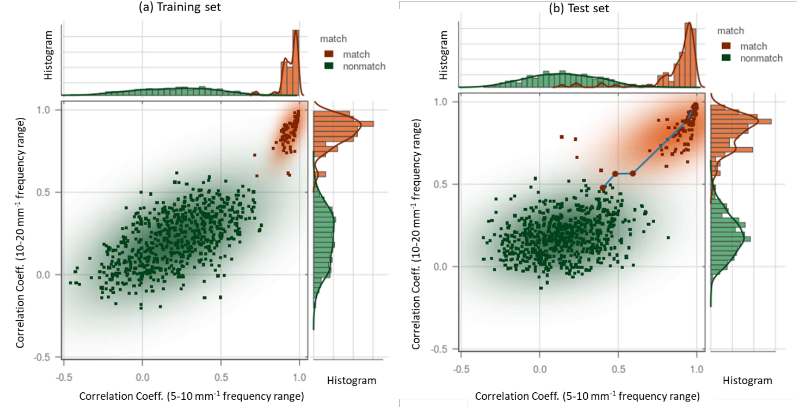
Analy in Fourier Domain



(a) (b)

- Correlation between spectra from corresponding images on tip and base surfaces in different radial frequency bands calculated.
    - image pairs for when the tip and base surfaces from same knife are *true matches*
    - pairs from when the tip and base surfaces from different knives are *true non-matches*
- This is our dataset.

Correlation Analy of FFC: Ob



- 81, 648 match/non-match correlations
- 1 range $\Rightarrow$ matches/non-matches imperfectly separated
- Training set: Matches/non-matches distinct w/ both ranges
- Test set: 1 true match correlation not separated
  - individually separated with correlations from all 9 pairs

Constructing Match Rule - General Strategy

- Rule uses correlations from image pairs in training set
  - QDA classifier trained to identify matching base and tip pairs on set of correlations in 5-10μm^{-1}.
  - logistic regression classifier with a weakly informative prior was trained for 10-20μm^{-1}.
- Rule classifies correlations from image pairs in training set
  - yield 18 match probabilities for each base-tip pair.
    - 9 from 5-10μm^{-1} + 9 from 10-20μm^{-1}.
  - projecting onto the first PC of 18 probabilities for the set of base-tip pairs.
  - LDA classifier trained on 1D projection to produce a final probability that the given base-tip pair are a match.

Logistic Regre - Modeling

- $c_{ijk}^{(10-20)}$ corr. in $10 - 20\mu m^{-1}$, kth image of base-tip i, j
- $M_{ijk} \sim \text{Ber}(p_{ijk}^{(10-20)})$ is 1 if image k on base i and tip j have same origin, 0 o/w

$$f(m_{ijk} | p_{ijk}^{(10-20)}) = {p_{ijk}^{(10-20)}}^{m_{ijk}} (1 - p_{ijk}^{(10-20)})^{1-m_{ijk}}, m_{ijk} \in \{0, 1\}, p_{ijk}^{(10-20)} \in (0, 1).$$

- assumed logistic regression model:

$$\log \left(\frac{p_{ijk}^{(10-20)}}{1 - p_{ijk}^{(10-20)}} \right) = \beta_0 + \beta_1 c_{ijk}^{(10-20)}.$$

  - M_{ijk} are independent across bases, tips, and images.

- Complete separation between matching & non-matching image pairs may make logistic regression inestimable.
- Gelman et al (2008): Bayesian logistic regression with default priors on β_0 and β_1.
  - scale $c_{ijk}^{(10-20)}$ to have mean 0 and SD 0.5
  - $\beta_0 \sim \text{Cauchy}(0, 10)$; $\quad \beta_1 \sim \text{Cauchy}(0, 2.5)$
    - fit model by incorporating approximate EM into usual IWLS (Gelman et al., 2008)
- estimated probability of an image match:

$$\hat{p}_{ijk}^{(10-20)} = \frac{1}{1 + \exp\{-\hat{\beta}_0 - \hat{\beta}_1 c_{ijk}^{(10-20)}\}}.$$

Combining Prediction Probabilitie

- Each of 9 base-tip image pairs yields set of probabilities of match
  - combine into single probability of whether base-tip pair are from same knife.
  - image-level probabilities highly correlated with each other,
    - global match model needs to account that some images from matching/non-matching pairs have low/high correlations
  - first perform PCA in order to summarize the variability in the (highly-correlated) predicted match probabilies
- LDA on first PC of predicted match probabilities
  - $p^*_{ij} \sim N(\eta_1, \tau^2)$ if base-tip (i, j) match w.p. ζ
  - $p^*_{ij} \sim N(\eta_2, \tau^2)$ w.p. $1 - \zeta$ if not
- Base i and tip j are match w.p.

$$\hat{\pi}_{ij} = \frac{\hat{\zeta} f(p^*_{ij} | \hat{\eta}_1, \hat{\tau}^2)}{\hat{\zeta} f(p^*_{ij} | \hat{\eta}_1, \hat{\tau}^2) + (1 - \hat{\zeta}) f(p^*_{ij} | \hat{\eta}_2, \hat{\tau}^2)}$$

Re

- Training image and surface level models on training set and predicting match probabilities on test set yields match probabilities (within $< 10^{-10}$) of 0 or 1.
- Predict match between (i, j) if $\hat{\pi}_{ij} > 0.5$, yields:

		Predicted Class	
		Match	Nonmatch
True Class	Match	9	0
	Nonmatch	0	72

- Reversing roles of training/test set yields similar results.

Conclusions and Further Work

- Fracture mechanics in objectively predicting match of evidence fragments
  - obtained base-tip image pairs
  - identified and used correlations between structure in spectral domain to identify pairs
  - used QDA and Bayesian logistic regression to predict match probability
  - perfect accuracy with quantified confidence on test sets.
- Extension to other kinds of materials
  - number of image pairs on surfaces?
  - effects of aligned/non-aligned image pairs
  - non-contiguous surfaces?