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Author(s):	Donald Gantz, Ph.D.
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Statistical Error Estimation for an Objective Measure of Similarity to a Latent Image

Principal Investigator:
Donald Gantz, PhD
Emeritus Professor of Statistics
Volgenau School of Engineering
George Mason University
4400 University Dr.
Fairfax, VA 22030-4422
Tel: (703) 278-8579
Email: dgantz@gmu.edu

Applicant/Recipient Organization:
Donna Senator
Associate Director, Proposal & Award Management
Office of Sponsored Programs
George Mason University
4400 University Dr. MS 4c6
Fairfax, VA 22030-4422
Tel: (703) 993-4806
Email: ospgrant@gmu.edu

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Summary of the Project

The goal of the Grant Project is to understand the structural and asymptotic statistical properties of the data modeling demonstrated in the Grant Proposal and to exploit state-of-the-art computational resources and modern methods of statistical analysis to make statistically well-founded assessments of the rarity of individualizing information relative to a Latent Image.

The Forensic Science problem at issue is that the assessment of latent prints from crime scenes is based largely on human interpretation and that claims that these assessments have zero error rates are not scientifically plausible.[1]

The Grant has exploited the technology underlying the LatentSleuth[2] Latent Fingerprint Examination Workstation to:

- Define an Objective Measure of Similarity of any fingerprint to a Latent Image;
- Use a large, randomly selected set of known non-mate images to the Latent to create a model predicting random similarity to the Latent Image;
- Demonstrate the prediction of random similarity to a Latent Image using images from the NIST SD 27 Special Data Base[3] and additional images.

The Grant Research relates to the following scenario for Latent Fingerprint Examination:

- A Region of Interest (ROI) is specified in the Latent Image.
- The Latent ROI is *consistent with* the quality areas of a particular exemplar image of interest.

[1] *Strengthening Forensic Science in the United States, A Path Forward*, National Research Council of the National Academies, 2009.
[2] LatentSleuth is a fingerprint analysis, visualization and matching tool designed to assist Latent Print Examiners in the analysis of latent prints.
[3] The National Institute of Standards and Technology, in collaboration with the FBI, has published NIST Special Database 27 (SD27) Fingerprint Minutiae from Latent and Matching Tenprint Images.

Therefore, the scenario for modeling is that it provide support for a Latent Print Examiner's (LPE's) report concerning a Latent Image and a specific exemplar.

The Grant research has shown that it is computationally feasible to warp[4] the Latent Image to a large set of known non-mate fingerprints for the Latent Image. Hence, it is has been computationally feasible for the Grant to measure similarity to the Latent Image for a large set of known non-mate fingerprints for the Latent Image. The measured similarity from a large set of known non-mate fingerprints that are randomly selected from a fingerprint data base will statistically represent the measured similarity for all fingerprint images in the data base. **The Grant research uses an Objective Measure of Similarity applied to a large set of known non-mate fingerprint images, randomly selected from a data base, to statistically estimate a *data base Random Match Probability* (RMP) for a specific Latent Image.**

Figure 1 illustrates WARPs of a Latent Image to two fingerprints – a ground truth mate image and a known non-mate image. The WARP maps the entire Level 2 ridge pattern[5] of the Latent Image *on top* of the Level 2 pattern of the fingerprints. Using WARPs, Level 2 characteristics in the Latent Image are measured for how closely they match in any fingerprint image.

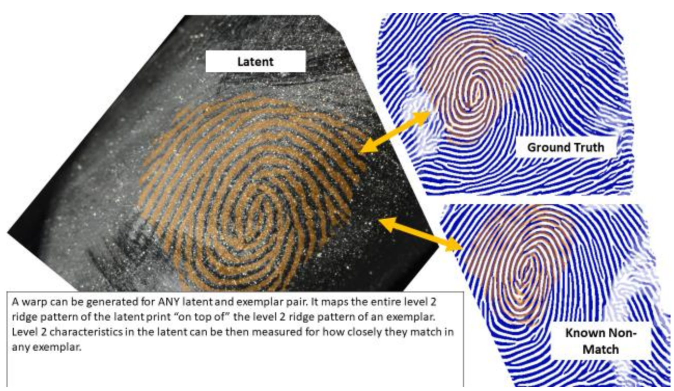


Figure 1

[4] Warping via LatentSleuth maps the entire Level 2 ridge pattern of the latent image on top of the Level 2 ridge pattern of an exemplar fingerprint.
[5] "Second level detail is much more than the specific location of where a ridge terminates at a ridge ending or bifurcation, or its Galton points." Ch 9, Examination Process, *Fingerprint Sourcebook*, NCJ Number 225320, 2011.

Figure 2A illustrates traditional similarity measurement for a ground truth mate image using minutia points (bifurcations and ridge endings). The Figure indicates *low error* similarity measurement for the ground truth mate image. Figure 2B illustrates traditional similarity measurement for a known non-mate image using minutia points (bifurcations and ridge endings). The Figure indicates *mixed error* similarity measurement for the ground truth mate image.

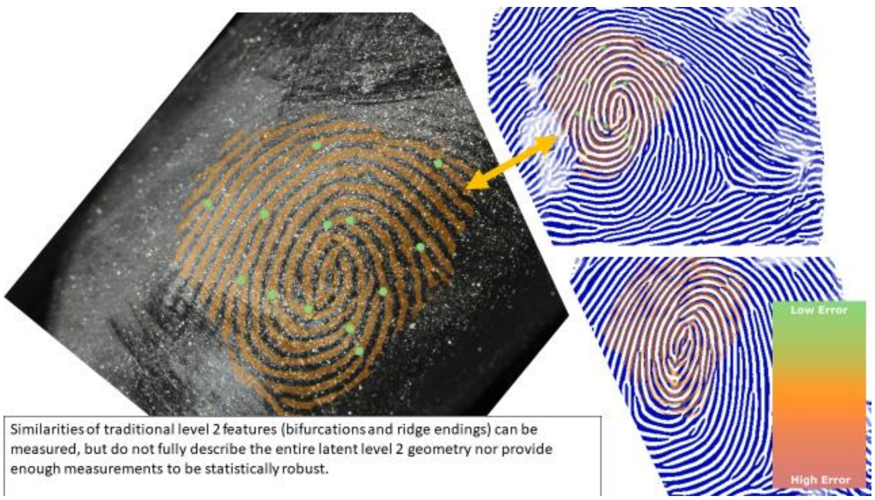


Figure 2A

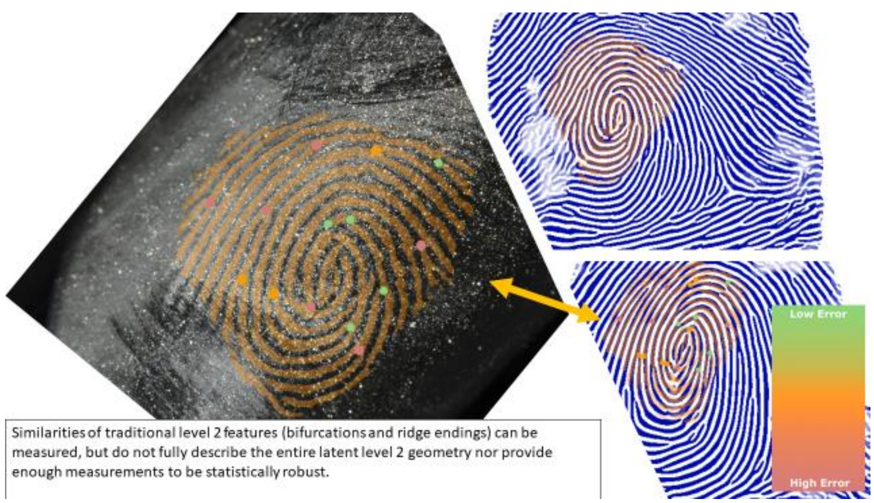


Figure 2B

In striking contrast to the illustrations in Figures 2A and 2B, a comprehensive measurement of Level 2 characteristics in the images makes possible the measurement of similarity to a Latent Image illustrated in Figures 3A and 3B. These Figures illustrate the continuous *low error* measurement of Level 2 similarity across the ground truth mate image and the continuous *mixed error* measurement of Level 2 similarity across the known non-mate image. The continuous measurement of Level 2 similarity provides a more complete measurement of Level 2 similarity to the Latent Image. Importantly, the continuous measurement of Level 2 similarity provides much more data for analysis and statistical modeling.

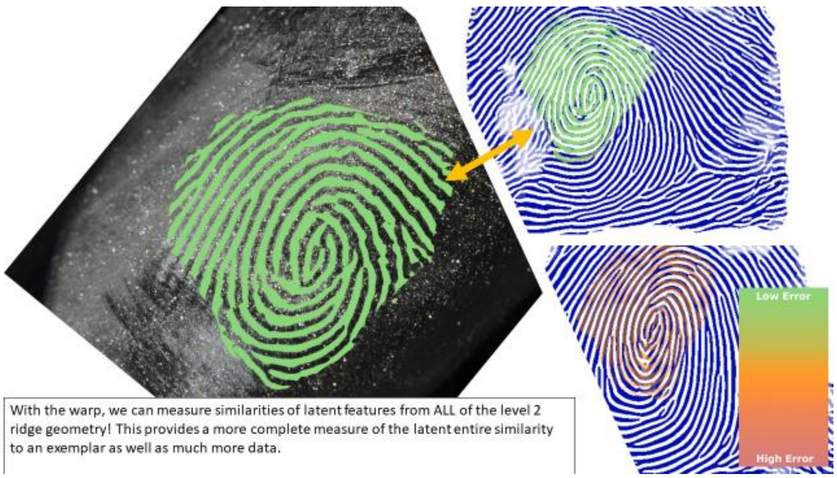


Figure 3A

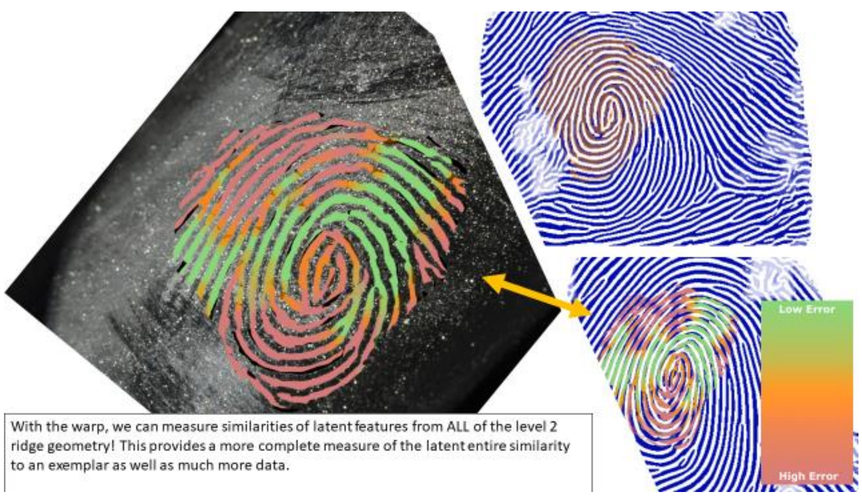


Figure 3B

The LatentSleuth technology creates a powerful quantification of Level 2 characteristics that provides the ability to find the best orientation and location for overlaying the Level 2 characteristics of the Latent Image onto any particular fingerprint image. This Grant has exploited that quantification of Level 2 characteristics to compare fingerprint images based on errors in their Level 2 similarity to a Latent Image. Further, the Grant's data analyses do the comparison continuously and comprehensively across the full Level 2 ridge geometry of the Latent Image. The Grant's data analyses exploit a *Principle of Similarity*: A true mate image to the Latent Image will *outcompete* non-mate fingerprint images when competition is based on the measured similarity of the Latent Image's Level 2 characteristics to those of the competing fingerprint images. The Grant's Principal Investigators have previously exploited the Principle of Similarity in their successful invention and research concerning writer identification where they used a novel quantification of handwriting to create the data analysis algorithms underlying the FlashID[6] workstation for document examiners.

The technology that WARPs the Level 2 characteristics of the Latent Image to any fingerprint image is the basis for the Grant's *Objective Measure of Similarity* to the Latent Image for a fingerprint Image. The definition of the Objective Measurement of Similarity is deferred to a later section of this Report. This section continues with an illustration of the Objective Measurement of Similarity being applied to a large set of known non-mate images to the Latent Image for the purpose of creating a model to predict the random Level 2 similarity of a fingerprint image to the Latent Image. Figure 4 is an illustration of WARPs of the Latent Image to a large set of known non-mate images to the Latent Image. It was stated above that this research has demonstrated that it is computationally feasible to do this WARPing to a large set of fingerprints.

[6] FlashID is a unique handwriting analysis, matching and visualization tool for document comparison and evaluation. It is a product of Sciometrics, LLC in Chantilly Virginia.

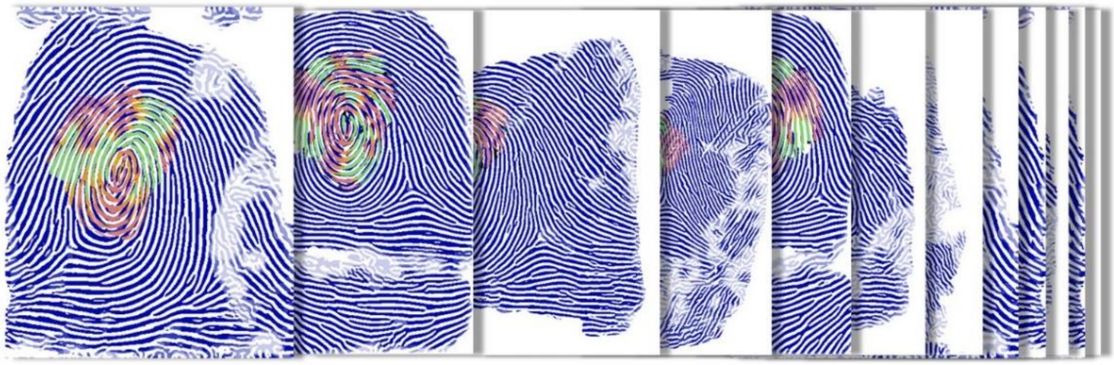


Figure 4

The Objective Measure of Similarity for one fingerprint image is a score resulting from using data analysis to *hierarchically* boil down tens of thousands of micro similarity scores to a single value. Later sections of this Report demonstrate how the data analyses create the conditions that lead to Objective Similarity Measurements from a large, randomly selected set of known non-mate fingerprint images providing the data for a valid model to predict a fingerprint's random Level 2 similarity to the Latent Image.

Figure 5 illustrates the derivation of the prediction model from the WARPs of the Latent Image to a large, randomly selected set of known non-mate fingerprint images. We can physically describe the Objective Similarity Measurement data as a two-sided (or two-tailed) indicator of similarity. By design in the quantification, the left side (tail) of the generated data is the side of increasing similarity to the latent. The data analysis algorithm captures the statistical characteristics of this left side of the generated data in order to predict non-mate similarity to the Latent Image.

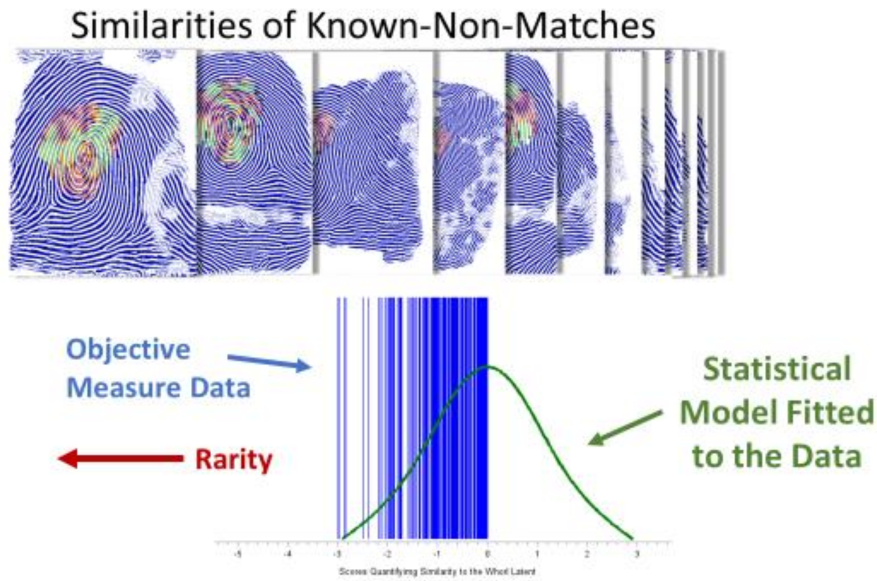


Figure 5

The model is used to predict the rarity of the Objectively Measured Similarity of any exemplar of interest. Figure 6 presents an illustration of the model predicting the rarity of the Objectively Measured Similarity of a ground truth mate to the Latent Image. The Objective Measure of Similarity to the Latent Image is computed for the ground truth mate exactly as that Measure had been computed for the non-mates to build the model.

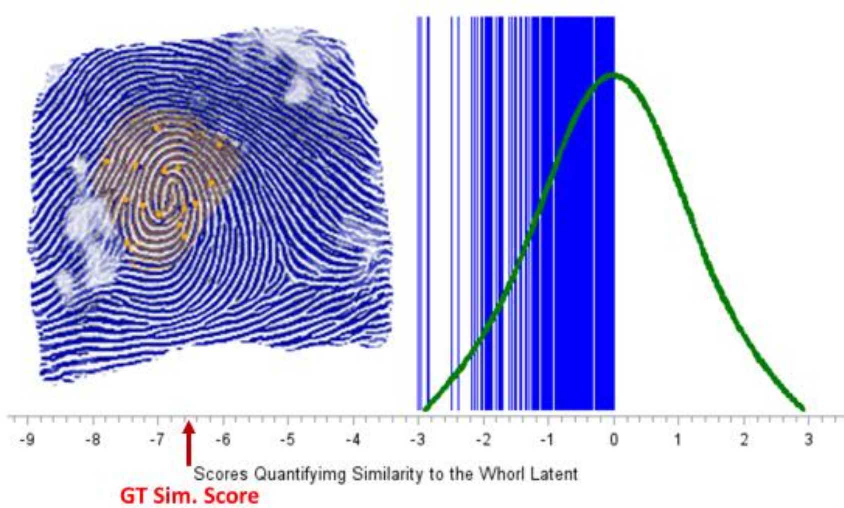


Figure 6

The model is a well-defined normal curve distribution; and the computed Measure (-6.56) for the ground truth image, has a normal p-value of 2.8621E-11 which equates to a rarity of 1 in 37 billion (See Figure 7). The model is *continuous* in the sense that any particular predicted value has probability zero; that is, there is zero area under the model curve over the particular value. The p-value is the probability (measured by area under the model curve) of a prediction at least as far to the left, the direction of rarity, as the computed value for the ground truth mate. The predicted p-value by the model is used by the research to compute the rarity of measured similarity to the Latent Image for an exemplar fingerprint image.

Conservative Prediction of Rarity of the Similarity to the Latent: < 1/37 Billion

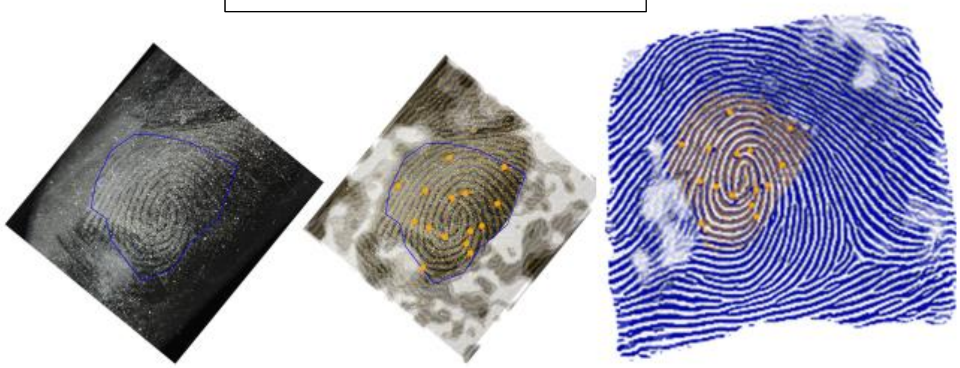


Figure 7

The Statistical Model is a *Null Model* in that it *predicts rarity* for the Objective Measure of Similarity to the Latent Image when it is computed for any *non-mate* fingerprint image. A very small rarity prediction for the fingerprint of interest *contradicts the Null Model* and suggests that the fingerprint image is, in fact, a true mate.

The predicted rarity for a fingerprint exemplar is *conservative* in that it is derived from an analysis of Level 2 characteristics only. It is further conservative in that the Objective Measure of Similarity is a measure of how well a fingerprint image covers the Level 2 characteristics of the Latent Image. The Objective Measure of Similarity does not rule out the possibility that a latent print examiner will find an exclusionary Level 2 feature in the measured fingerprint image that is being compared to the Latent Image.

Definition and Modeling of the Objective Measure of Similarity to a Latent Image

The first significant challenge for the Grant research was to define an Objective Measure of Similarity between a latent image and a non-mate fingerprint, where the measure is going to be computed for a large number of known non-mates.

A *Base Set Model* is an initial quantification of the similarity between a latent image and a small set of known non-mate fingerprints to the latent image. This quantification provides a base of data that describes *spurious*[7] similarity to the latent image by a non-mate fingerprint. The Objective Measure of Similarity to a Latent Image by a non-mate fingerprint is computed by *competing* the non-mate fingerprint versus the Base Set Model. Therefore, the Objective Measure quantifies similarity to a Latent Image *relative to* a Base Set Model. **The Objective Measurement of a large number of randomly selected known non-mate fingerprints will provide a general model for *random similarity to a Latent Image.***

Grant subawardee Sciometrics[8] randomly selected tens of thousands of known non-mate fingerprints from a very large fingerprint image database, and then competed these fingerprints against Base Set Models of latent similarity to provide data for the statisticians. Statisticians observed that the statistics that are computed using the data from non-mate fingerprints could be statistically modeled as having a partially-normal distribution. That is, the empirical distribution of the statistic (e.g., a hierarchical median) is a combination of a normally distributed (similarity) part and a (dissimilarity) part that skews one side of the data into a longer tail.

[7] The term 'spurious similarity' is used here to refer to unstructured similarity whereas the term 'random similarity' is used in the Report in the context of a result from a formally designed statistical model for prediction.
[8] Sciometrics, LLC is located in Chantilly Virginia and is a developer of novel biometric and forensic technologies. Their LatentSleuth technology is exploited by the research Grant.

The statisticians created an algorithm for capturing the normally distributed part of the non-mate Objective Measure data distribution. The normally distributed part of the distribution was then used to calculate a p-value for the Objective Measure of the ground-truth mate for the latent. The Objective Measure for the ground truth mate was computed via competition with the Base Set Model in identical fashion to the Objective Measurement of non-mate fingerprints.

The Grant effort consisted of four tasks.

Task 1: Define the approach to creating a *Measure of Similarity* that quantifies a fingerprint image's ability to cover the Level 2 characteristics in a Latent Image.

The LatentSleuth technology provides a WARP of the latent image to any candidate fingerprint image. The WARP:

- is a *mathematical function* that maps the entire latent image (all locations) onto the reference fingerprint image;
- provides a distortion free overlay of the latent onto the candidate image;
- is *invertible* and the *inverse function* maps the reference fingerprint image onto the latent image;
- makes it possible, *at each location*[9] on the Latent, to compute a 'latent overlay error' for the WARP.

The measure of a fingerprint's similarity to a Latent Image is founded on comparisons of Level 2 characteristics using latent overlay errors. The 'latent overlay error' is a measure of how closely the latent overlay (i.e., the WARP of the Latent Image) and the fingerprint image conform relative to Level 2 features (inclusive of location and local curvature).

[9] The locations in a latent are sampled at 1/500th of an inch along the ridge and furrow skeletons of a processed latent image.

The introduction above described the need to perform a first step of quantifying similarity to a Latent Image using a small Base Set of known non-mate fingerprints to the Latent Image. This quantification yields a Base Model of the *spurious* similarity of the latent image to an arbitrary non-mate fingerprint. The framework for building the Measure of Similarity starts with using WARPs to quantify Level 2 similarity to the Latent Image for the known non-mate fingerprints in the Base Set. An algorithm for computing pair-wise comparisons of similarity among Base Set images yields a massive amount of data from the Base Set that provides the basis for defining the Objective Measure of Similarity to the Latent Image. The data is massive since all pairs of Base Set Images are compared for similarity at all *locations* in the Latent Image ROI. A new fingerprint image of interest (to which the Latent Image has been WARPed) will be pair-wise compared to each Base Set image to yield data that, when injected into the Base Set only data, will provide enhanced data from which to compute the Objective Measure of Similarity for the new fingerprint.

The Objective Measure of Similarity for a new fingerprint image is then a measure *relative to* the images in the Base Set. Semi-Annual Grant Project Reports demonstrated that the ultimate modeling of random similarity to a Latent Image is extremely robust to the makeup of the images forming the Base Set. The Grant team based this conclusion on extensive testing concerning the number of images for the Base Set as well as the ways to select the Base Set images. A specific example later in this Report demonstrates the robustness of the modeling results relative to the choice of specific images for the Base Set. For this Report, all modeling is done using a common Base Set of 50 known non-mate fingerprint images. Although the research determined that a 30 image Base Set was adequate, going to 50 images seemed prudent as it amounted to a negligible computational increase. The finding of the current research that a common Base Set will suffice for modeling similarity for any Latent Image is important to the exportation of the techniques of this research to the broader Latent Print community.

In the following presentation, the *ReferenceSet* refers to a large, randomly selected set of known non-mates to the Latent Image. The tabular structure in Figure 8 illustrates the basic structure of the data underlying the data analysis algorithm.

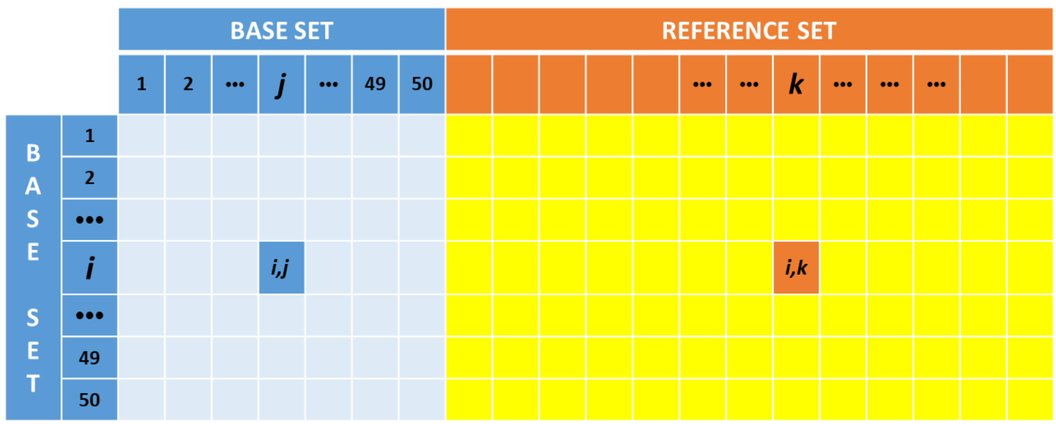


Figure 8

In summary, the latent print image is WARPed, via the LatentSleuth technology, to each of the fingerprint images comprising a Base Set as well as to each fingerprint image in a Reference Set. **Via the WARPs, all Base Set images will compete among themselves for accuracy of coverage of the latent image's Level 2 features.** This competition among Base Set images for similarity to the latent image yields the massive amount of data that is the basis for defining the Objective Measure of Similarity to the Latent Image for additional fingerprint images.

The symbol omega, ω, will represent a location in the latent. For all pairs of Base Set Images at any location ω in the latent, we compute Pairwise Competitions for accuracy of coverage of the latent image's Level 2 features. We also compute Pairwise Competitions between each Reference Image and all Base Set Images at each location ω in the latent. **Reference Set images *do not* compete against each other!** Figures 9A and 9B display the pairwise competition patterns and formulas. Figure 9A describes pairwise competitions between Base

Set images. Figure 9B describes pairwise competitions between Reference Set images and Base Set Images.

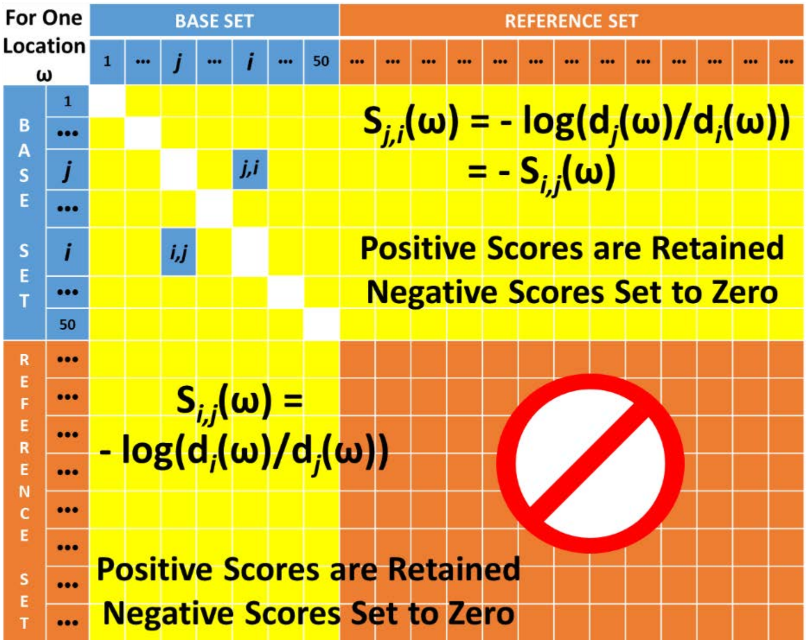


Figure 9A

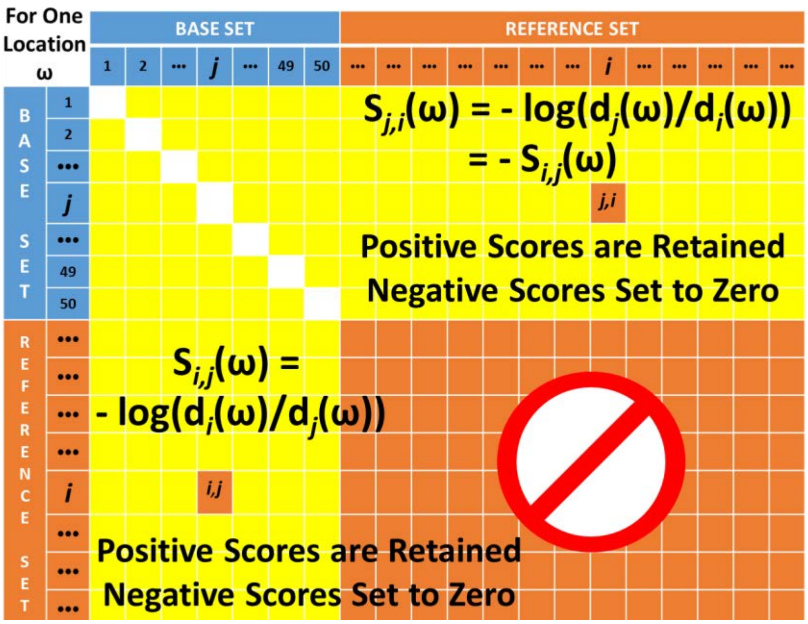


Figure 9B

In Figures 9A and 9B, the symbol $d_j(\omega)$ represents the latent overlay error of image *i* at location ω of the latent image. The score $S_{i,j}(\omega)$ is the pairwise competition score between images *i* and *j*. Note that $S_{i,j}(\omega) = - S_{j,i}(\omega)$.

At each location ω in the Latent Image, there are 1,225 positive pair-wise competition scores from competitions between images in the Base Set. There are thousands of locations ω in the Latent Image for which pair-wise competitions are computed for the Base Set images. **Therefore, the pair-wise competitions between Base Set Images at locations in the Latent Image result in millions of pair-wise competition scores that together capture the Base Set Images' spurious similarity to the Latent Image.** Independently, each Reference Set Image enters a pair-wise similarity competition with each Base Set Image to create tens of thousands of scores that capture that Reference Image's *relative* similarity to the Latent Image. The *relative* similarity of the Reference Image to the Latent Image is *relative* to the measured similarity of the Base Set images to the Latent Image.

A complex computational algorithm operates on the massive amount of pair-wise similarity data just described to compute an Objective Measure of the Similarity of the Reference Image to the Latent Image. The algorithm's objectively computed output for one Reference Image *k* consists of 2,450 $z^j_{i,k}$ scores where:

i is the ID of a Base Set Image; and

j is the ID of a second Base Set Image.

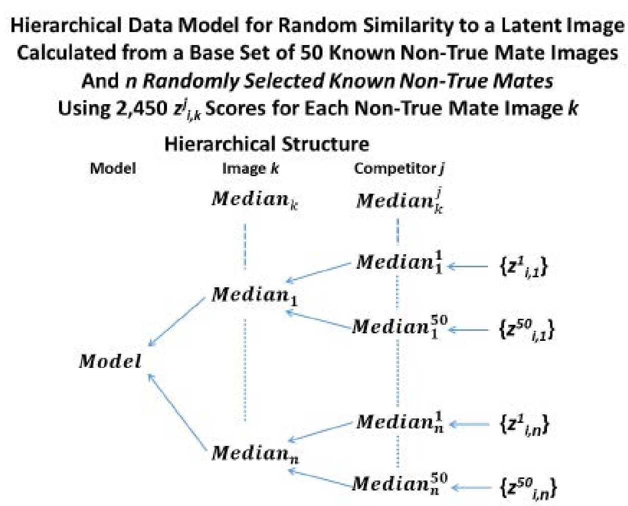
Each $z^j_{i,k}$ score is a weighted average of measured similarity across all locations in the Latent Image. A particular $z^j_{i,k}$ score summarizes the difference in the competitiveness of images *k* and *i* when these images have the common pair-wise competitor image *j* from the Base Set.

Statistics computed from the 2,450 $z^j_{i,k}$ scores for image *k* will be referred to as Objective Measures of the Similarity of the Reference Image *k* to the Latent Image. The Objective

Measure requires only that an ROI be identified in the Latent Image; no Examiner feature identification is required. The process is automated.

The Similarity Data from computing the Objective Measure of Similarity for a large randomly selected set of known non-mates to the Latent Image is used to create a model that will predict a *Data Base Random Match Probability* for any fingerprint Image. Although the Objective Measure of Similarity is relative to a Base Set of images, the prediction model based on computing the Objective Measure of Similarity for a large randomly selected set of known non-mates will be independent of the Base Set. That is, **the Model's Rarity Prediction for the Objective Measure of any new Fingerprint Image will be independent of the Base Set used to define the Objective Measure.**

For this Report, the hierarchical median of the 2,450 $z^j_{i,k}$ scores is the statistic used to define, for a Reference Image *k*, an Objective Measure of Similarity to a Latent Image. The Diagram below describes the hierarchical structure of the 2,450 $z^j_{i,k}$ scores. First, 50 medians over *i* values are computed, one median for each fixed Base Set Image *j*. Second, the Objective Measure of Similarity for Reference Image *k* is computed as the median of the 50 *j*-Medians., The hierarchical Medians from a large, randomly selected set of known non-mates to the Latent Image are used to create the statistical Model to predict random similarity to the Latent Image.



Task 2: Define the full computational structure of the *Objective Measure of Random Similarity* to a Specific Latent Image.

Task 2 involves the definition of a complex computational algorithm that starts with the pair-wise competition data described in Figures 9A and 9B and culminates with the computation of the penultimate $z^j_{i,k}$ scores. The details associated with Task 2 are very complex, and for the purposes of this Research Report, we proceed directly to the Task 3 Section which presents examples of modeling random similarity with the hierarchical median of the 2,450 $z^j_{i,k}$ scores.

Task 3: Demonstrate the Computation of a *Model of Random Similarity* to a Specific Latent Image by Computing the Objective Similarity Measure for 1,000s of Randomly Selected Non-Mate Images.

The current section of the Report presents substantive insights into the structure of the 2,450 $\boldsymbol{z^j_{i,k}}$ scores that summarize Level 2 similarity to a Latent Image for a fingerprint image *k*. The section presents graphic summaries that reveal details of the hierarchical structures of the scores and the statistical properties this brings to the ultimate overall hierarchical Median. The notion that only one tail of the Median scores is informative concerning similarity to the Latent Image introduces the requirement for a defined procedure that successfully locates and exploits that tail of scores. This section presents a procedure that has worked for the more than thirty examples that the team analyzed in detail and whose results are summarized in this Report.

The data used in this section's demonstrations comes from analyses of the SD 27 Latent U260 and the reported ground truth mate to that Latent Image. Of 20,000 known non-mate fingerprint images processed by Sciometrics for this example, 18,753 provided computable Objective Similarity data for the U260 image.

The Grant team computed hierarchical median statistics from the 2,450 $z^j_{i,k}$ scores for each image *k.* The first hierarchical computation is to take the median of the 49 $z^j_{i,k}$ values for fixed *k* and *j*. We use the notation Median_j to represent this first stage median. Then we compute the overall Median of the 50 Median_j scores for image *k*, and refer to this as the Median.

Figure 10 presents Median_j data for the U260 example's sampled non-mate images that have overall Median scores less than -1.5. The scores are plotted with a vertical axis indicating the overall Median for the image *k* relating to the Median_j score. The graph is enhanced by red '+' symbols at vertical values for the overall Median scores; hence the red symbols fall on a straight line. The Figure shows that the images become more sparse for more negative overall Medians. **The trailing off of negative Medians should be reflective of the statistical rarity of more extreme levels of similarity to the Latent Image in the data base from which the 20,000 *k* images were selected.**

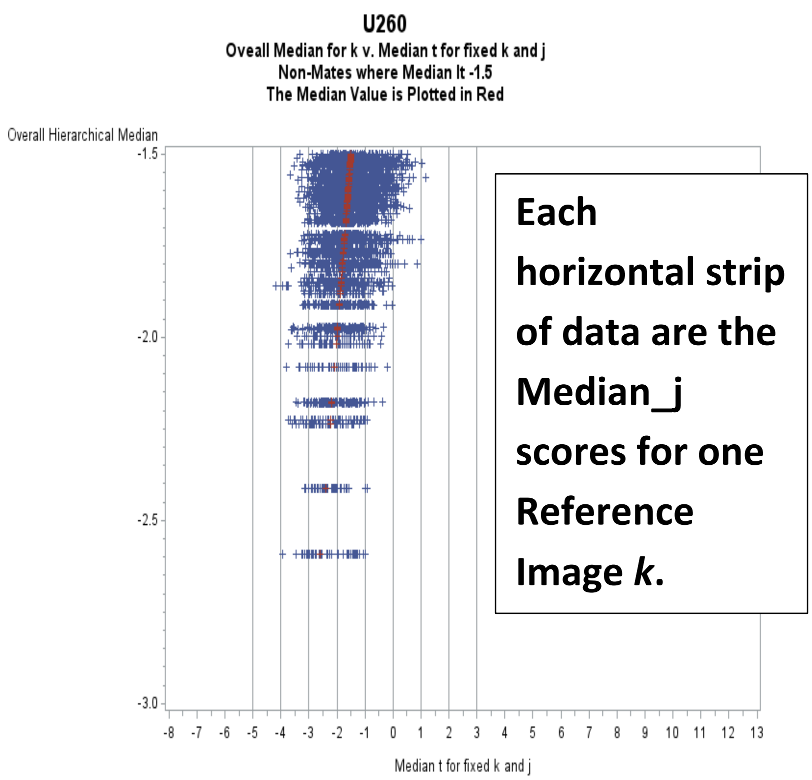


Figure 10

Figure 11A includes all Median_j scores (937,650 = 50 times 18,753) for the U260 example. Further, the overall Median of the corresponding image *k* is indicated with a red '+' symbol; and the 50 Median_j scores for one image *k* = 2388 are indicated with orange '+' symbols. Figure 11B presents a histogram of the same Median_j data that is plotted in Figure 11A. The two Figures 11A and 11B provide informative views concerning the Median_j data. **In particular, the cloud of data in Figure 11A corresponds to the mounded, right-skewed histogram in Figure 11B.**

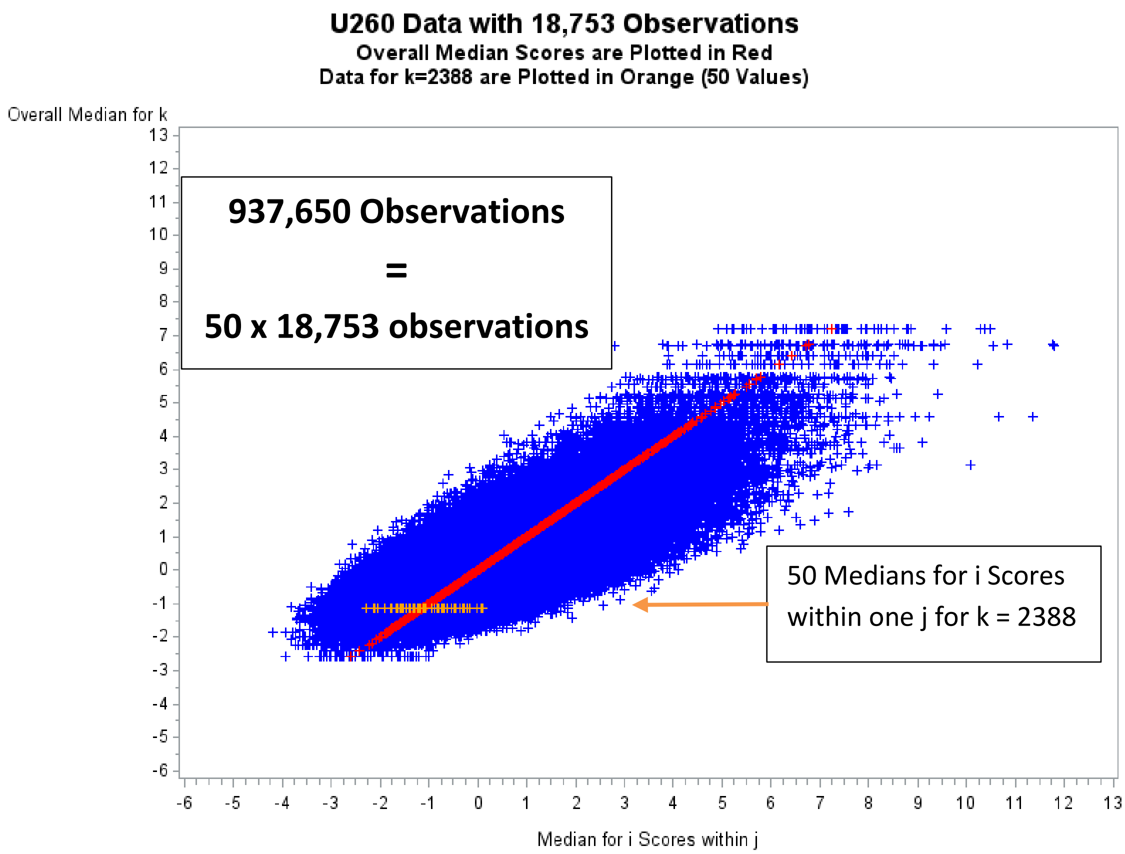


Figure 11A

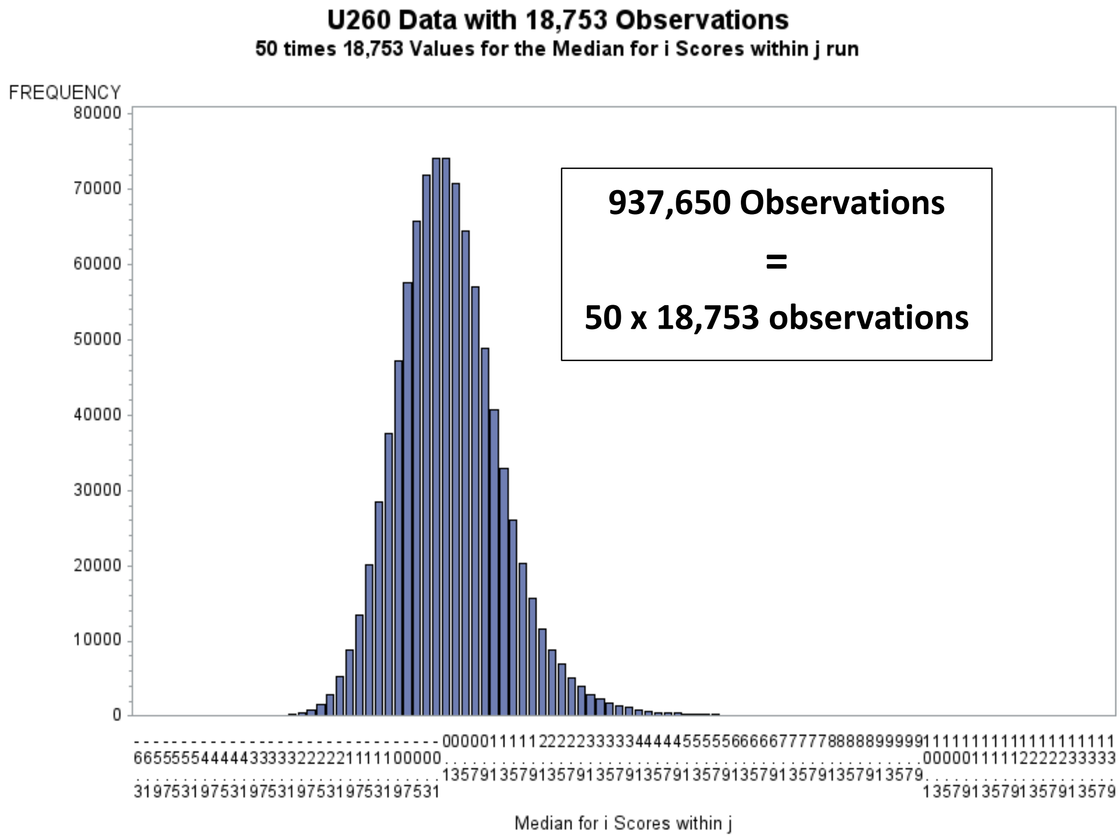


Figure 11B

Figure 12A presents a subset of the data displayed in Figure 11A. This subset consists of the data where the overall Median is less than .69125; this is 80% of the data displayed in Figure 11A. Subsetting the data is the first step towards using the data to model random similarity to the Latent Image. Figure 12B presents a histogram of the subset of data displayed in Figure 12A. The histogram in Figure 12B is mounded and very symmetric.

Figure 12C presents a histogram for the 15,002 overall Median values for the data presented in Figures 12A and 12B. The histogram in Figure 12C is mounded and short-tailed on the right; the median value for the Medians in the histogram is -0.10828.

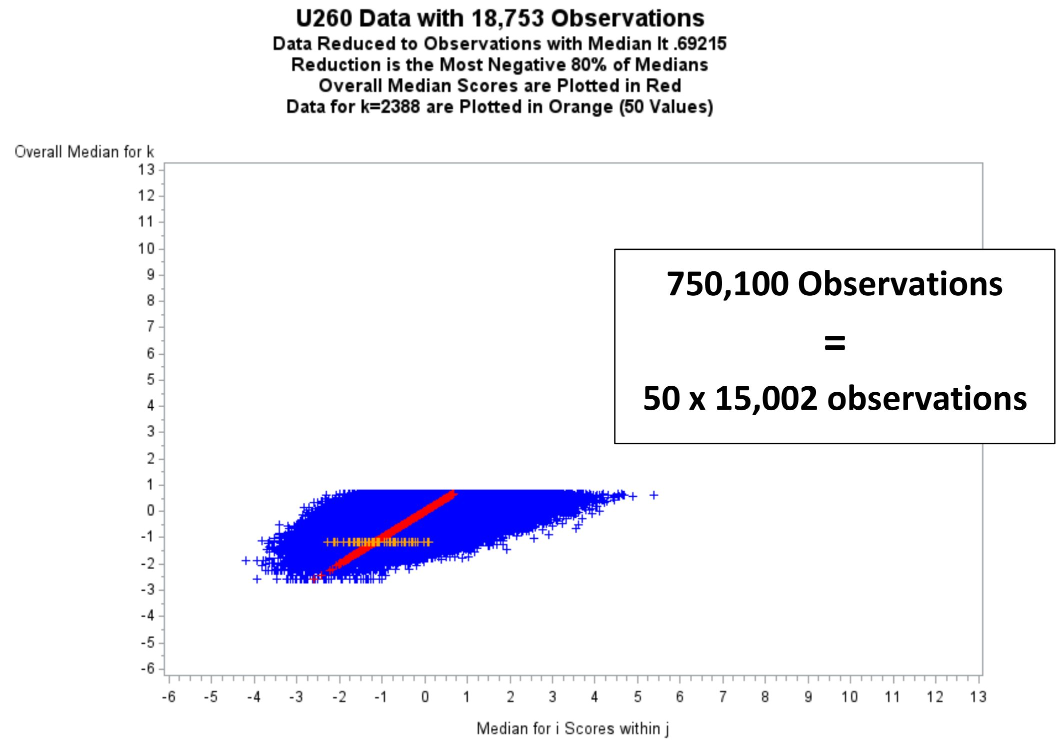


Figure 12A

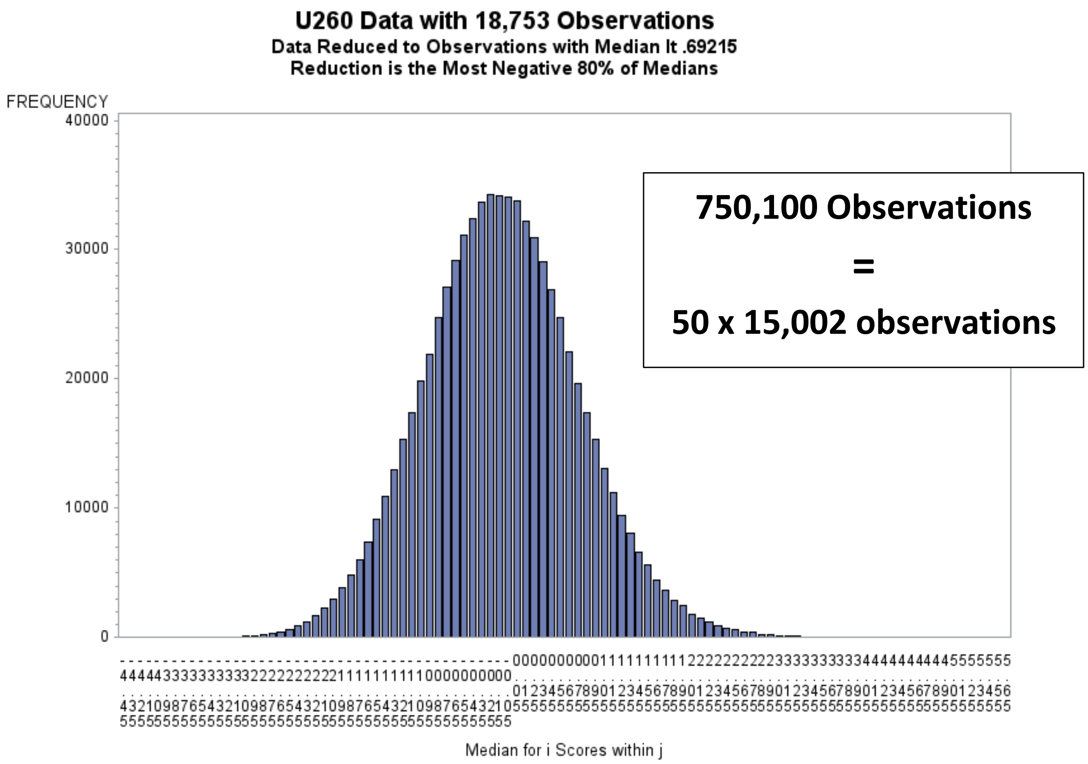


Figure 12B

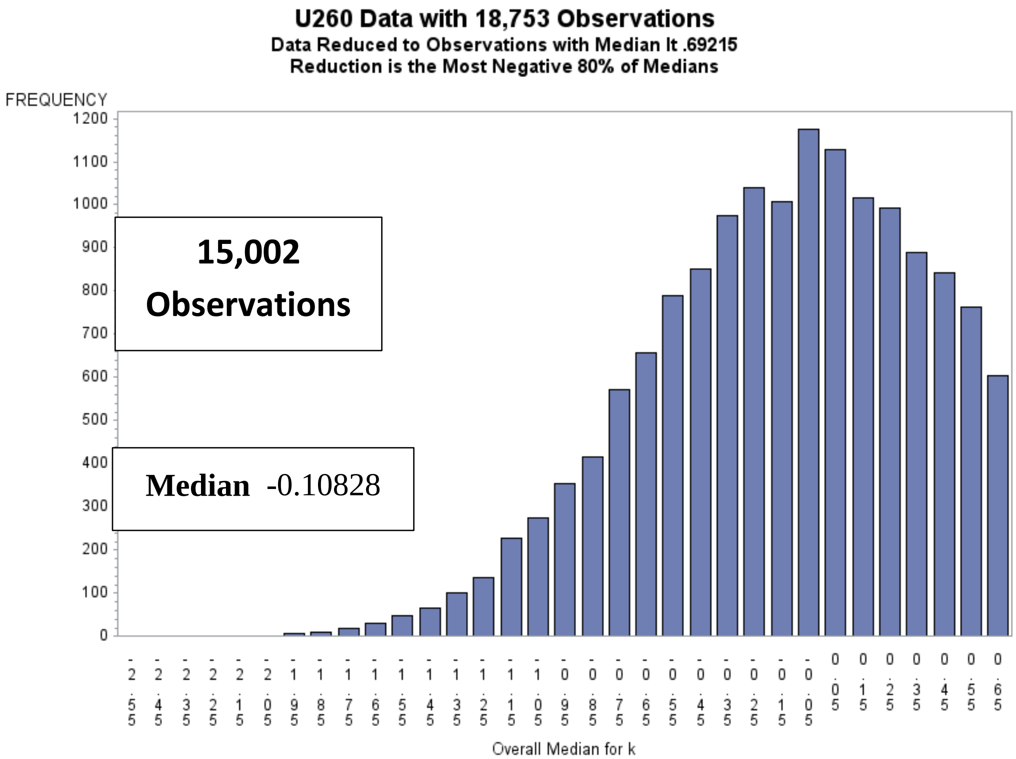


Figure 12C

Figure 13A presents a subset of the data displayed in Figure 12A. This subset consists of the data where the overall Median is less than -0.10828; this is half of the data displayed in Figure 12A and 40% of the data displayed in Figure 11A. Subsetting the data to half of the data displayed in Figure 12A is the next step towards using the data to model random similarity to the Latent Image. Figure 13B presents a histogram of the subset of data displayed in Figure 13A. The histogram in Figure 13B is mounded and very symmetric.

Figure 13C presents a histogram for the 7,501 overall Median values for the data presented in Figures 13A and 13B. The histogram in Figure 13C is a ‘left tail’ only from the histogram presented in Figure 12C.

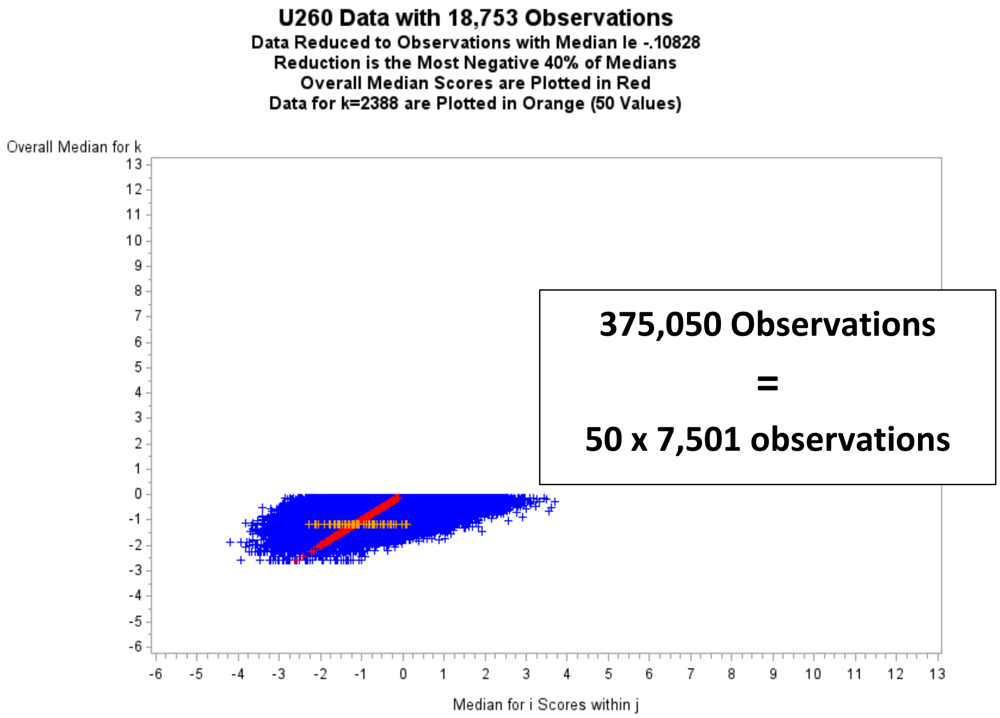


Figure 13A

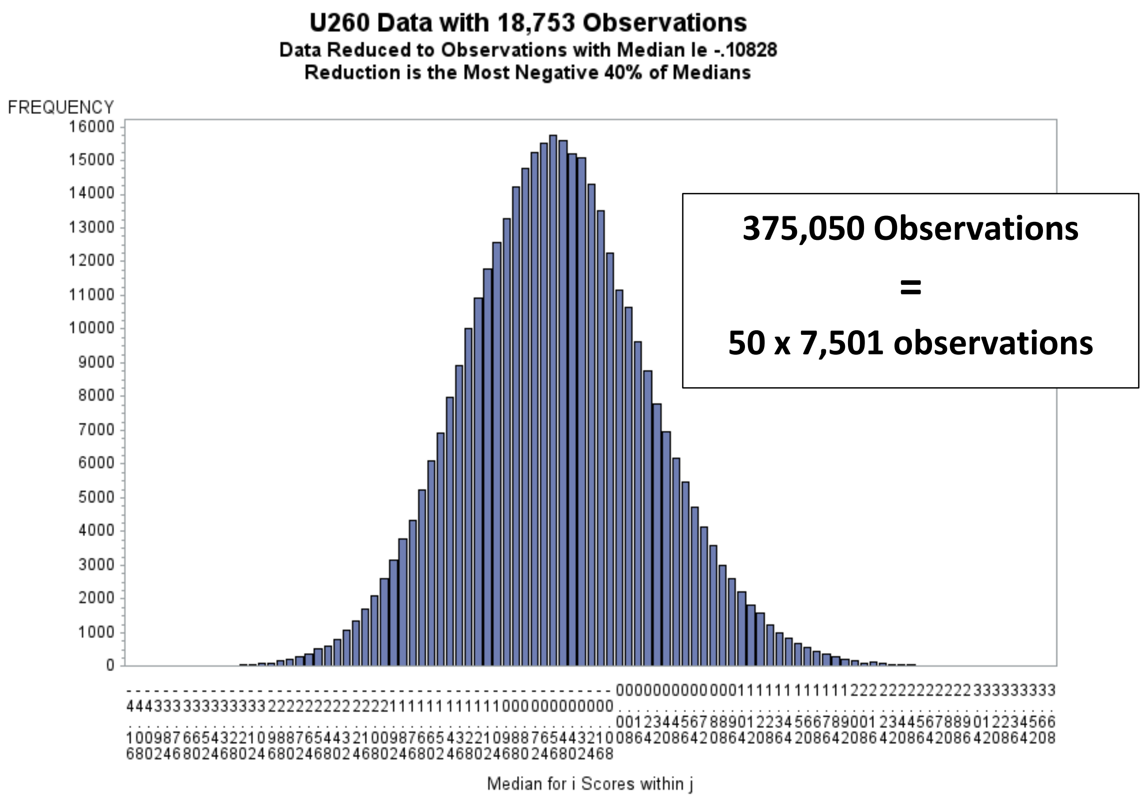


Figure 13B

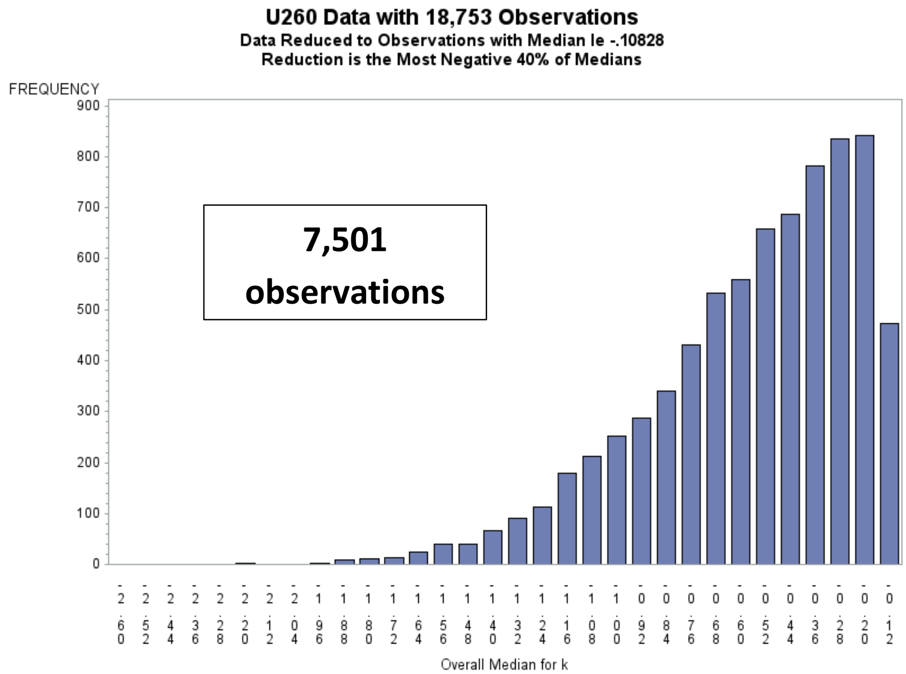


Figure 13C

Figure 14A presents a histogram of the Median_j data from Figure 13B which has been augmented by adding the data generated by reflecting the Median_j data from Figure 13B to the right side of -.10828. Hence, the histogram in Figure 14A is mounded and symmetric. Figure 14B presents a histogram of the overall Median computed from the data in Figure 14A. The histogram in Figure 14B is mounded and symmetric; also, the data from Figure 14B passes Tests for normality:

Tests for Normality

Test	**Statistic**		**p Value**	
Kolmogorov-Smirnov	**D**	0.004257	**Pr > D**	>0.1500
Cramer-von Mises	**W-Sq**	0.043549	**Pr > W-Sq**	>0.2500
Anderson-Darling	**A-Sq**	0.266616	**Pr > A-Sq**	>0.2500

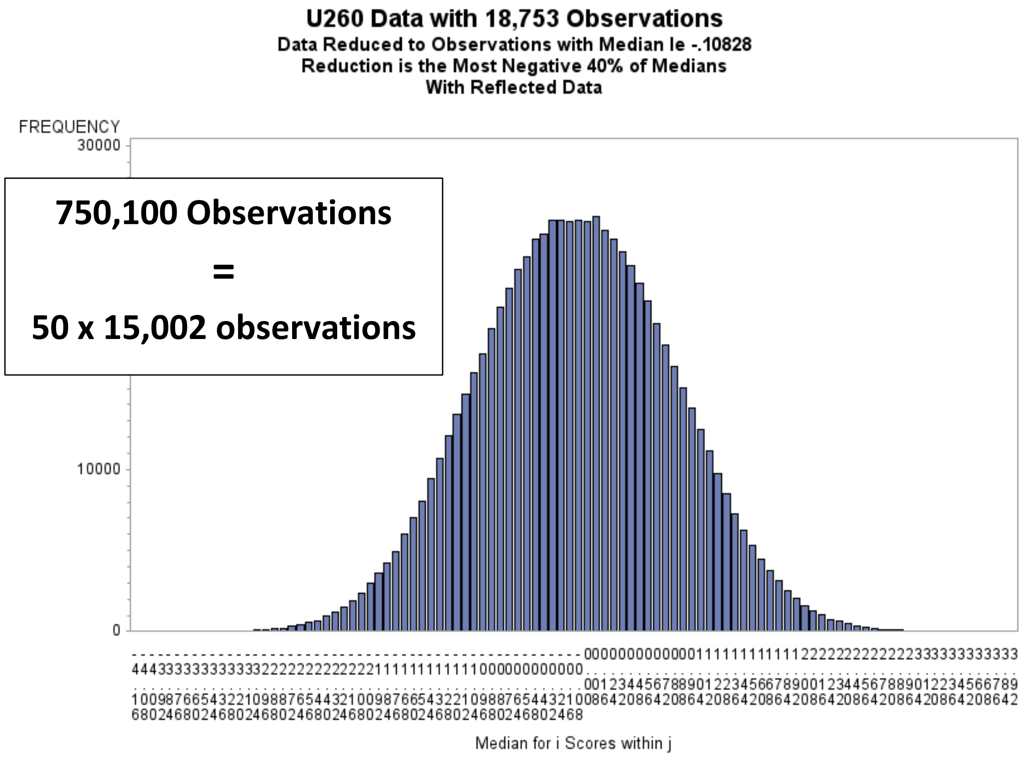


Figure 14A

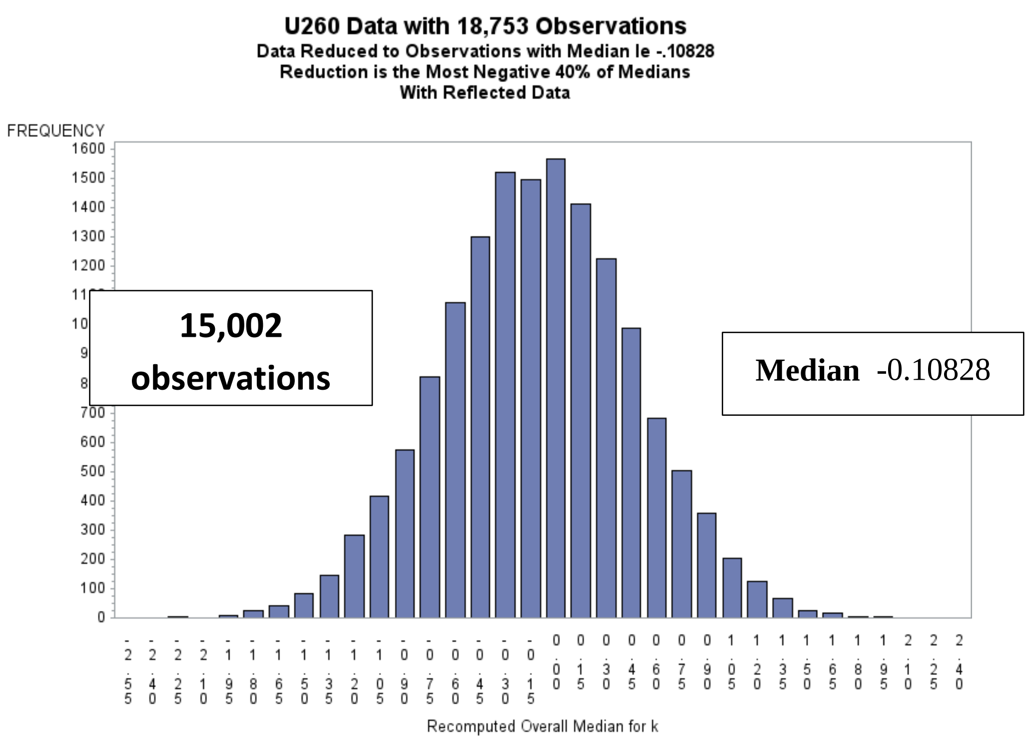


Figure 14B

We now standardize the data displayed in Figure 14B by first subtracting the mean (-0.10828) and then dividing the result by the standard deviation (0.57694984). Figure 14C presents a histogram for the standardized data.

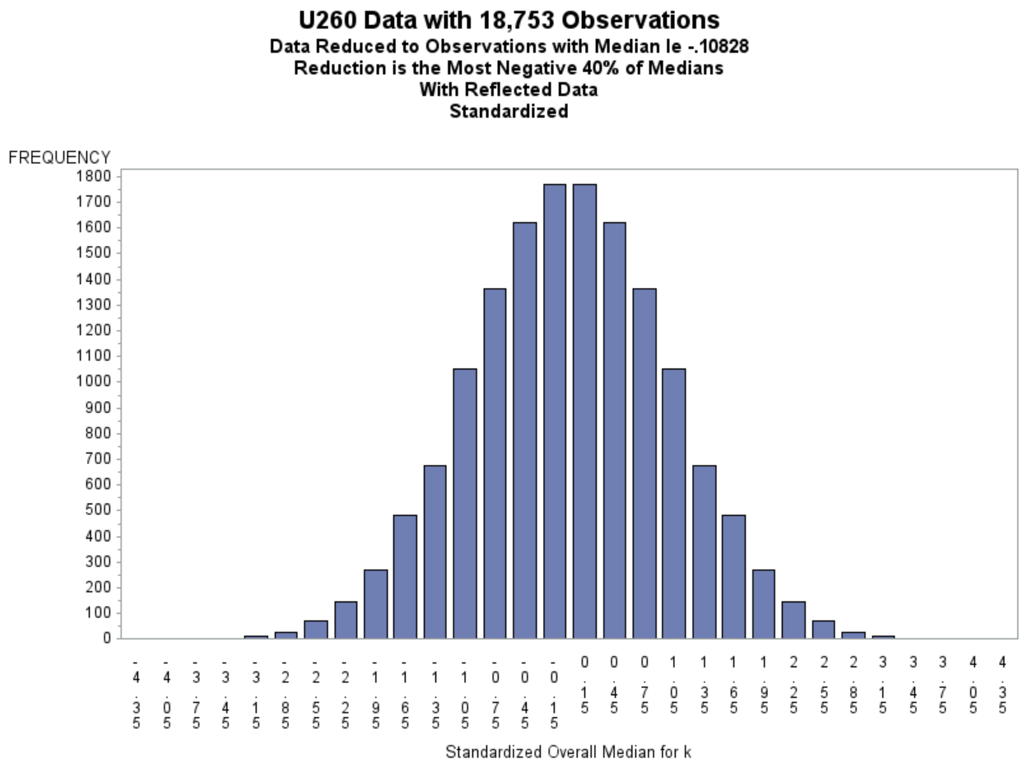


Figure 14C

The Objective Measure (Hierarchical Overall Median) calculated for the ground truth mate image is -4.1789. Performing the same calculations on this ground truth score as was done to standardize the data for the Base Set only images, the resulting ‘Standardized Score’ for the ground truth image is -7.055414037. The p-value for -7.055414037 calculated from the Standard Normal Distribution is 8.604377E-13. The reciprocal of the p-value is 1,162,199,175,291. Therefore, the Predicted Rarity is 1 in 1,162,199,175,291.

For this modeling for the Latent Image U260, the reduction to the most negative 80% of hierarchical Median scores produces a valid model for use of the Normal Distribution to predict rarity. The following Table summarizes the corresponding data reductions used for modeling other Latent Images. The remainder percentages range from 50% to 100%.

Remainder Percentages for 33 Latent Images

Remainder %	Frequency	Percent	Cumulative Frequency	Cumulative Percent
50	1	3.03	1	3.03
57	1	3.03	2	6.06
70	1	3.03	3	9.09
73	1	3.03	4	12.12
76	2	6.06	6	18.18
78	2	6.06	8	24.24
80	1	3.03	9	27.27
81	1	3.03	10	30.30
82	1	3.03	11	33.33
86	2	6.06	13	39.39
88	2	6.06	15	45.45
93	2	6.06	17	51.52
95	1	3.03	18	54.55
97	2	6.06	20	60.61
98	2	6.06	22	66.67
99	2	6.06	24	72.73
100	9	27.27	33	100.00

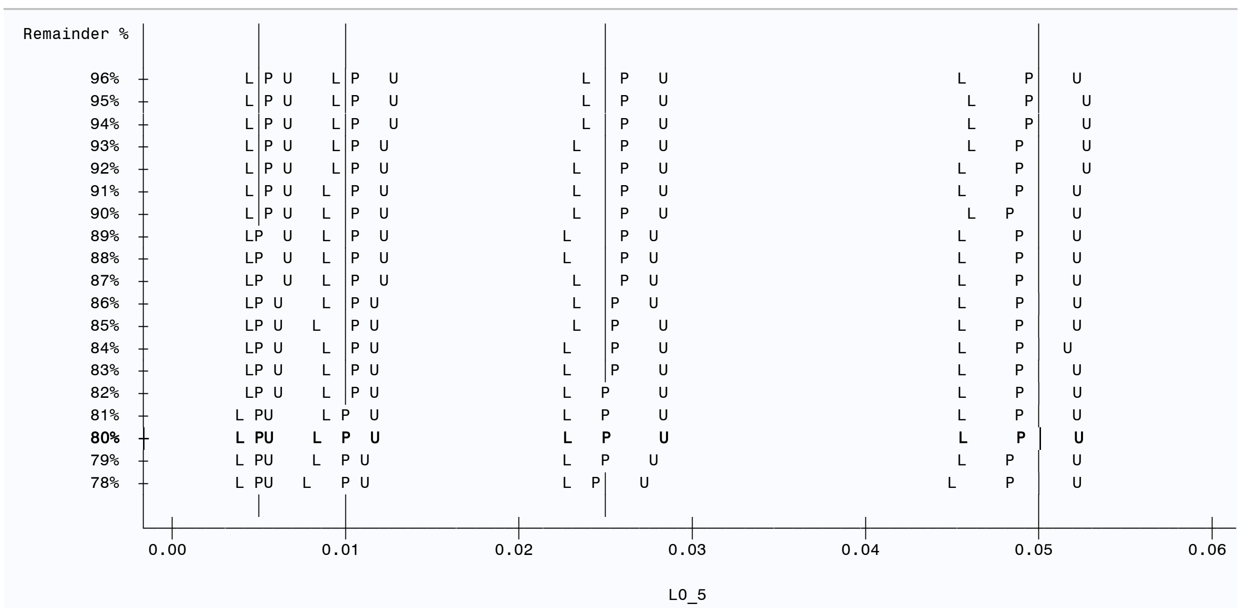
Selection of an appropriate remainder percentage for a particular Latent Image used three sets of summary information computed for the hierarchical Median statistics. The first type of summary information is the following list of *reduction information* for possible remainder percentages from 65% to 100%, continuing with the U260 example. The list below presents just the remainder percentages that *pass* the Normal Test (p-value = .15). These are the *acceptable* candidate remainder percentages from this summary.

U260

Remainder Percent	Score	Test	Test_Prob	P_Value	Rarity
78	-7.13112	0.005748	0.15000	4.9778E-13	2,008,924,023,996
79	-7.09281	0.004613	0.15000	6.5707E-13	1,521,899,004,753
80	**-7.05537**	**0.004260**	**0.15000**	**8.6069E-13**	**1,161,864,294,637**
81	-7.03082	0.004132	0.15000	1.0266E-12	974,060,824,157
82	-6.99225	0.005161	0.15000	1.3526E-12	739,343,288,100
83	-6.98771	0.003617	0.15000	1.3971E-12	715,781,392,016
84	-6.97068	0.003093	0.15000	1.5771E-12	634,093,651,364
85	-6.95253	0.003667	0.15000	1.794E-12	557,426,704,606
86	-6.92414	0.003332	0.15000	2.1932E-12	455,963,228,547
87	-6.89486	0.003861	0.15000	2.6959E-12	370,933,316,360
88	-6.88731	0.004140	0.15000	2.8429E-12	351,751,610,208
89	-6.87527	0.004987	0.15000	3.0937E-12	323,235,091,475
90	-6.85087	0.004775	0.15000	3.6702E-12	272,465,412,327
91	-6.83684	0.005322	0.15000	4.0479E-12	247,041,438,476
92	-6.81521	0.005202	0.15000	4.7064E-12	212,476,022,077
93	-6.79718	0.005343	0.15000	5.3342E-12	187,469,204,126
94	-6.76102	0.004732	0.15000	6.8512E-12	145,960,891,845
95	-6.74392	0.004811	0.15000	7.7087E-12	129,723,231,538
96	-6.72384	0.005094	0.15000	8.8495E-12	113,000,269,829

The second type of summary information is the following plot of *reduction information,* again for possible remainder percentages from 65% to 100% continuing with the U260 example. This summary below contains plots of *Percentile Point estimates* (P) and distribution free *95% Confidence Limits* (L=lower limit & U=upper limit) for the percentiles (.005, .01, .025, .05) of the reduced and modeled (as done above) hierarchical Median data; just the remainder percentages that pass the Normal Test are listed. A later graphical display will demonstrate that the *flow* seen in the plots of percentile estimates is largely due to differences in the far left tail of the reduced data. The information in the two summaries is both consistent and complementary. Note that the 80% remainder lines of these two summaries are bolded. The second summary allows for a *reasonable* selection of a remainder percentage among percentages where the Normal Test is passed with p-value = .15. **Note from the first summary that the choice of remainder percentage is not *knife edge* in that the range of remainder percentages close to 80% predict the same order of magnitude for the Rarity of the ground truth image's Level 2 similarity to the Level 2 structure of the Latent Image.**

U260



A third type of summary information is the following table of *reduction information*; again the table lists just the remainder percentages that pass the Normal Test. This summary contains *Percentiles* calculated from the reduced and modeled (as done above) hierarchical Median data.

Percentiles for Remainders from 78 to 96 Percent of 18,753 Observations for U260

Remainder %	Reduced Obs	Min.	Prob. Min.	P .005	P .01	P .025	P .05	P .10	P .25	P .50
78	14627	-4.33707	.000007220	-2.59354	-2.33174	-1.96492	-1.65981	-1.27864	-0.66551	0
79	14815	-4.32075	.000007775	-2.58964	-2.32998	-1.96439	-1.65915	-1.27975	-0.66918	0
80	**15002**	**-4.30484**	**.000008355**	**-2.57893**	**-2.32017**	**-1.96088**	**-1.65671**	**-1.27905**	**-0.67217**	**0**
81	15190	-4.29562	.000008710	-2.57934	-2.32184	-1.96163	-1.65708	-1.28049	-0.67269	0
82	15377	-4.27894	.000009389	-2.57434	-2.31455	-1.95602	-1.65613	-1.27862	-0.67483	0
83	15565	-4.28010	.000009340	-2.57712	-2.31472	-1.95319	-1.65700	-1.27892	-0.67465	1.18381E-17
84	15753	-4.27466	.000009572	-2.57862	-2.31411	-1.95286	-1.65463	-1.27655	-0.67639	0
85	15940	-4.26857	.000009837	-2.57580	-2.30647	-1.95402	-1.65539	-1.27959	-0.67561	0
86	16128	-4.25699	.000010360	-2.57164	-2.30627	-1.95005	-1.65628	-1.27906	-0.67789	0
87	16315	-4.24488	.000010936	-2.56962	-2.30529	-1.94293	-1.65472	-1.27942	-0.68054	0
88	16503	-4.24420	.000010969	-2.56362	-2.30872	-1.93923	-1.65543	-1.27769	-0.68102	0
89	16690	-4.24113	.000011120	-2.56401	-2.31147	-1.94090	-1.65773	-1.27659	-0.67934	0
90	16878	-4.23147	.000011609	-2.55491	-2.30617	-1.93727	-1.65923	-1.27622	-0.68086	0
91	17065	-4.22721	.000011831	-2.55155	-2.30793	-1.93819	-1.65584	-1.27664	-0.68029	0
92	17253	-4.21884	.000012278	-2.54925	-2.30335	-1.93819	-1.65556	-1.27771	-0.68191	1.41963E-18
93	17440	-4.21239	.000012634	-2.54510	-2.30283	-1.94051	-1.65523	-1.27862	-0.68115	-7.0473E-19
94	17628	-4.19618	.000013572	-2.53660	-2.29886	-1.94104	-1.65223	-1.27848	-0.68405	0
95	17815	-4.19018	.000013937	-2.53754	-2.29761	-1.94262	-1.65224	-1.27931	-0.68608	0
96	18003	-4.18244	.000014420	-2.53746	-2.29628	-1.94253	-1.65067	-1.28050	-0.68469	0

Figure 15A presents all qqplots for 65% to 100% remainders using 10 percent smoothing splines for the modeled data. Note that all qqplots in Figure 15A are straight lines through the medians indicating, generally, a good fit there to the standard normal distribution. The qqplots differ in the far left tails. These differences are consistent with the pattern of point estimates and confidence intervals in the plot of the second summary above. Figure 15B presents the qqplot for deduction 80% for which the modeled data has a Normal Test p-value equal to .15 and which was selected to predict Rarity for of the measured similarity of the image of the reported ground truth mate to the Latent Image U260. The patterns among qqplots are consistent with the information in the three preceding summaries concerning reductions to the data. The qqplots in

Figures 15A and 15B visualize the adjustment to the tails of the reduced data as the remainder percentage changes.

qqplots for 65 to 100 Percent Remainder after Reduction

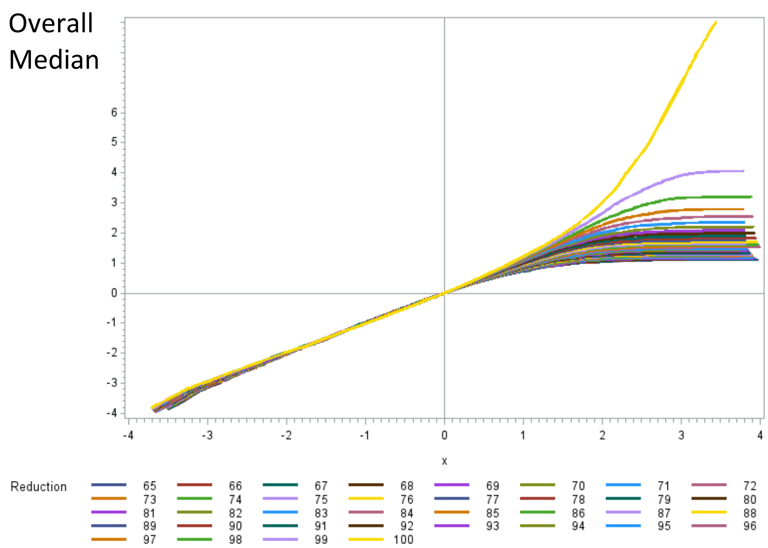


Figure 15A

qqplot for 80 Percent Remainder after Reduction

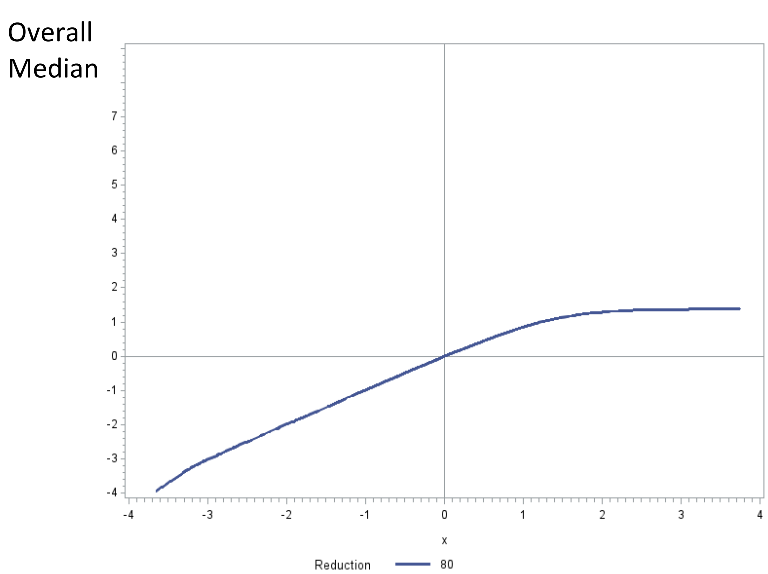


Figure 15B

Three informative summaries were presented to support the selection of an 80% remainder in the hierarchical Median score as the basis for modeling to create a predicted similarity of the ground truth mate image to the U260 Latent Image. These three summaries were computed for each analyzed Latent Image. The three summaries for each of the analyzed Latent Images were computed (via SAS® programs) by the Grant team in a span of about 15 minutes from when the hierarchical Median data was received from Sciometrics. The procedure is straight-forward and computationally feasible. The procedure was consistently applied to all analyzed Latent Images, resulting in remainder percentages from 50 to 100 percent, as were listed in a Table above.

We have demonstrated above that the competitive structure that gives us the $\boldsymbol{z^j_{i,k}}$ data values leads to a *statistically conditioned error model* that would consistently predict the rarity of any observed similarity between a reference print and the Latent Image ROI. *The competitive design of the data generation quantifies a reference fingerprint's similarity to a latent relative to the similarity jointly demonstrated by the Base Set Images*. Further, the similarity between each fingerprint and the latent is measured minutely across the entire Level 2 structure of the Latent Image ROI. That is, fingerprint images compete against the Base Set images for similarity to the latent *minutely across the Latent Image ROI*.

Because the similarity data comes directly from randomly selected known non-mate fingerprints and that random selection is the source of variability in the data, it is logically consistent that the model's *prediction of the rarity of the observed similarity to the latent* by any reference fingerprint should be a valid Data Base Random Match Probability relative to the fingerprint image data base for non-mate selection.

When a reference fingerprint image is actually a true mate to the latent, then that fingerprint image will out-compete the known non-mate images used to build the random similarity model. Further, the model will assess the deviation of the true mate's similarity from random similarity and make a credible prediction that a random non-mate fingerprint image from the reference fingerprint image data base would demonstrate the same degree of similarity as demonstrated by the true-mate image.

Robustness of the Base Set

We continue to use analyses concerning the Latent U260 from the NIST SD 27 Special Data Base to demonstrate the robustness of the modeling and rarity predictions relative to the images that comprise the Base Set. We use the 'best 50' known non-mate images that scored most similar to the Latent Image as the Base Set for a separate modeling exercise. The 'best 50' non-mate images are, in fact, the images whose data is used in Figure 10 above. The known non-mates for modeling are those from the previous modeling with the 'best 50' images removed.

The styles of summaries that are provided above for the initial analysis concerning Latent U260 were recreated for the new modeling and prediction using the 'best 50' images as the Base Set. The percentage remainder in the data for modeling is 76% using those summaries and the logic applied above.

The 'Standardized Score' for the Objective Measure (Hierarchical Overall Median) calculated for the ground truth mate image is -7.13324. The p-value for -7.13324 calculated from the Standard Normal Distribution is 4.9017E-13. The reciprocal of the p-value is 2,040,100,558,257. Therefore, the Predicted Rarity is 1 in 2,040,100,558,257.

As earlier, the choice of the data remainder percentage is not ‘knife edge’ with neighboring remainder percentages yielding similar results.

For the initial modeling for Latent Image U260 detailed earlier, the ‘Standardized Score’ for the Objective Measure (Hierarchical Overall Median) calculated for the ground truth mate image is -7.055414037. The p-value for -7.055414037 calculated from the Standard Normal Distribution is 8.604377E-13. The reciprocal of the p-value is 1,162,199,175,291. Therefore, the Predicted Rarity is 1 in 1,162,199,175,291.

The results using the ‘best 50’ and the results from the initial modeling are equivalent for practical purposes. The stability of the orders of magnitude of Rarity predictions is in very strong agreement both within and between the two modeling examples.

Recall that the Objective Measure of Similarity is similarity relative to a Base Set. With the original fixed Base Set, many of the sampled non-mates out-compete the Base Set for similarity to the Latent Image; however, with the ‘best 50’ Base Set, the sampled non-mates are out-competed by the Base Set. In both instances, the ultimate standardized models equally measure the data base random similarity to the Latent Image. Although the non-mate sample for the ‘best 50’ Base Set example lacks the tail of the most similar (to the Latent Image) 50 non-mates, the resulting model’s results agree with the results from the initial modeling where the non-mate sample included the 50 most similar non-mates.

Simulations

The Grant team could not find any published statistical methods to apply to building a prediction model from just part of the left tail of the data. Through data analysis, the team determined that, very robustly, some reduction in the data by eliminating the rightmost data would lead to a data model whose leftmost half of the data would have the strong statistical properties required for similarity modeling. We have defined a procedure, demonstrated above for Latent U260, to determine an appropriate reduction in data for modeling Rarity of an alleged True Mate image to a Latent Image. We have also applied that procedure to simulated data. The simulated data is *hypothetically* Objective Similarity data for a Latent Image and *hypothetically* the data is generated from 20,000 randomly selected non-mates to the Latent Image. The simulations start with 16,000 random observations from a standard normal distribution and 15,000 random observations from an exponential distribution. The objective measure data for the simulations takes the standard normal observations that are < .x and the exponential observations that are >= .x, for various values of x

In the cases with actual Latent Image data, the true Rarity of the alleged True Mate is unknown, and the analysis is an attempt to estimate it. In the simulations, we consider a known ground truth example value of -5 which, consistent with the standard normal leftmost tail of the mixed simulation data, has a p-value of 2.8665157E-7 and thus a Rarity of 1 in 3,488,556.

We perform the following six steps on the simulated data:

1. First, reduce the data to the leftmost (e.g., most negative) part of the data at 1 percent steps reducing the data to 65 to 100 percent of the data.

2. For each reduced set of data from Step 1, take the left-most half of that reduced percentage of the data and shift it so that it's right-most value becomes zero;
3. Third, reflect the data after step two symmetrically to the positive side of zero to double the size of the data and get a symmetric set of data.
4. Fourth, standardize the reflected data.
5. Fifth, compute Normal Distribution Fit Statistics to the standardized data, and use the standardized data to estimate rarity for an assumed true mate.
6. Sixth, compute and graph 95% (distribution free) confidence intervals for .5, 1, 2.5 and 5 percentiles of the standardized data.

For the simulations, we again consider the reductions that pass the Normal Test with a maximal test p-value of .15. Further, we study the *transition pattern* of confidence intervals to empirically determine an inflection point in the confidence interval transitions displayed above. Recalling the U260 example, the goal is to optimally adjust the tail of the modeled data by the selection of the remainder percentage.

The p-value and Rarity Prediction from a simulation are point estimates of true values. Another set of data from the same *hypothetical* population would also yield point estimates of the true values. Therefore, we considered issues of sampling variability and accuracy of point estimates using simulations. For instance, we executed additional iterations of the procedure for sampling from the *hypothetical* population and performed the analysis steps using a range of specific data reductions for modeling. For instance, the full reduction process was applied to each of 1,000 samples. After the reduction process, less than 5% of the 1,000 samples had Normal Test p-values less than .05.

Also, 90% of the 1,000 samples had Normal Test p-values equal to the .15 maximal p-value.

For practical application, a simulation's accuracy from an approximately 18,000 observation data set is adequate. **In any specific case for an actual Latent Image, the alleged True Mate p-value is unknown, but we believe that following the procedures outlined here to guide the selection of a data remainder percentage for a random sample of 20,000 known non-mates will result in a Rarity prediction for that case that will be accurate in practice.**

All together, the simulations from hypothetical data bases have demonstrated that the methods to determine an appropriate remainder percentage to the data are effective and that the modeling of the reduced data should provide an accurate estimate of the Rarity of the True Mate Image's measured similarity to the Latent Image.

Task 4: Use the NIST SD 27 Latent Database images to create examples of the Computation of the *Statistical Rarity* of the Ground Truth Mate Image using the Model of Random Similarity to the Latent.

The team had determined that it would be best to move our research forward by working with the more difficult latents from the NIST SD 27 'Good, Bad and Ugly' Latent Database. These would be the latents for which an examiner would have difficulty reaching a conclusion. Sciometrics ran the data analysis software on 20,000 randomly selected fingerprints for each of a group of selected latents. Their specialized LatentSleuth software WARPed the latents to the randomly selected fingerprints and computed the raw data that is described above in this report. In accordance with the team's decision from Task 1 discussed earlier in this Report, the same deterministically designed Base Set of 50 high quality fingerprint images was used for each latent.

The data analysis algorithms designed for this research yield 2,450 $z^{j}_{i,k}$ values for each of the randomly selected images *k*. Following the steps outlined above, the 2,450 $z^{j}_{i,k}$ values were reduced to a single *statistic* for the image *k* by hierarchically calculating medians of the $z^{j}_{i,k}$ values; first over *i* for fixed *k* and *j*, and then over *j* for fixed *k*. We refer to that hierarchically calculated median simply as the *Median Statistic*. We use the *Median Statistic* data from the 20,000 randomly selected fingerprints to build the rarity model for the latent.

Through data analyses with data that Sciometrics provided for latents, the team determined that, very robustly, the six steps, demonstrated above for example U260 and for simulations, would lead to a data model with the strong statistical properties required for similarity modeling.

After the six-step procedure, the Normal Distribution Fit Statistics and the confidence intervals for percentiles provide the information required to select an appropriate remainder percentage to use for similarity modeling. The choice of remainder percentage will not be *knife edge* as shown above in the example for U260. The procedure has worked well with the latents for which the Grant team has attempted model building using 20,000 randomly selected known non-mate fingerprints.

The procedure makes no prior statistical assumptions upon which to base the statistical model of similarity to a latent. Rather, any data used as a model for prediction is shown to demonstrate reliably close normal distribution properties so that it is reasonable to use a normal distribution for prediction.

The example presented above in this Report uses the latent image and reported ground truth true mate fingerprint image for latent U260 from the NIST SD 27 Database. For that example and for the additional Latent Images studied, the LatentSleuth workstation was used for automated image processing of both the latent and true-mate images. Then, again using the LatentSleuth workstation, the Sciometrics software developer made some edits to both the latent and the true-mate images. The software developer, who is an inventor of the Sleuth technology, has had several years of experience working with practicing latent fingerprint examiners (LPEs) internationally. *All edits were to make the examination process as realistic as possible and to bring our example into the realm of an actual LPE examination*. Reasons for editing include:

- Automatic image processing failed to pick up obvious Level 2 features in either image.
- The true-mate image had masked-out regions of bad quality within which it would not be competing with other images for similarity to the Latent Image.

The team considers such editing essential so that the conference presentations done so far and scheduled in the future with LPE experts are credibly related to their processes.

Continuing with the U260 example, Figure 31 presents the edited latent and true-mate images. The blue polygon over the latent image is the examiner selected region of interest (ROI) for the data analysis.

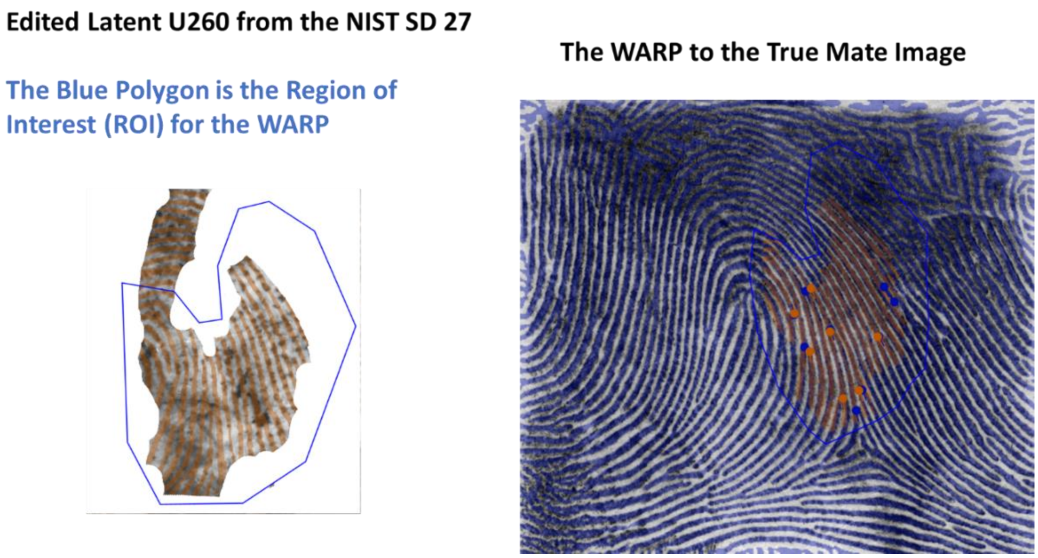
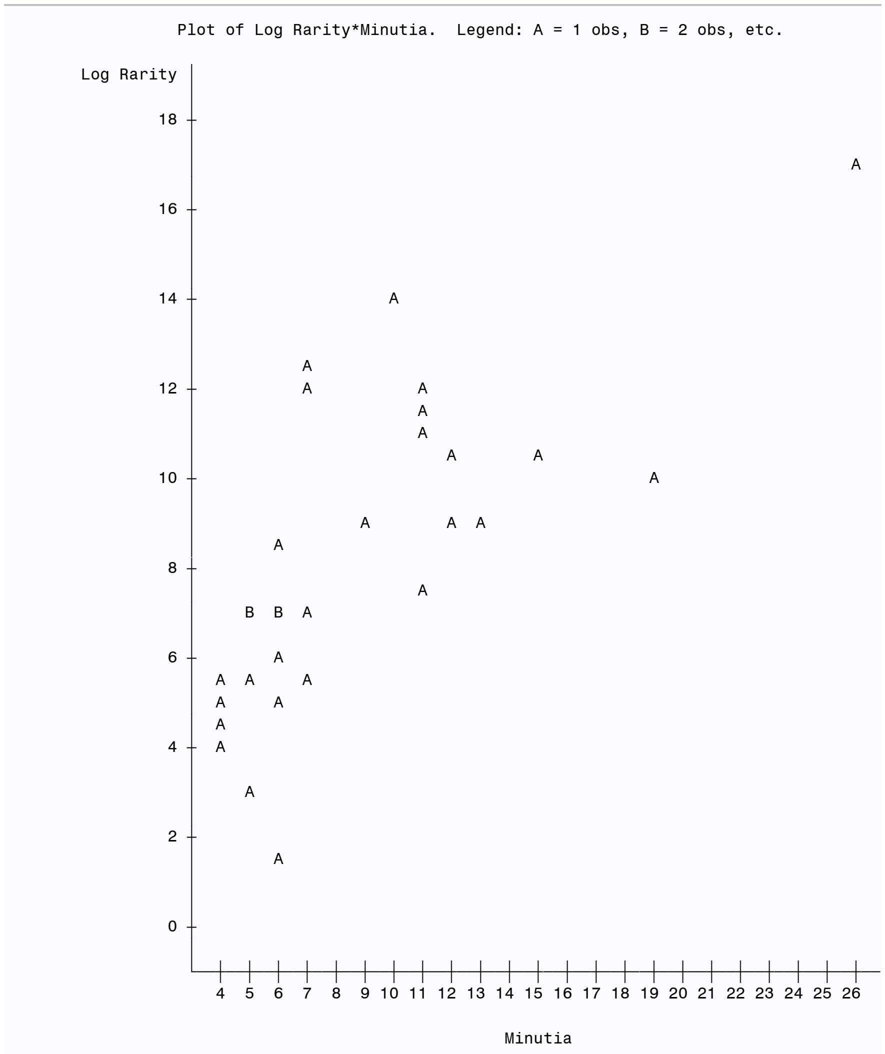


Figure 31

This Report, under Task 3, has already included details of modeling for U260 both with the common Base Set and with a Base Set consisting of the 'best 50' fingerprint images from the common Base Set modeling. The U260 example has 7 matched minutia points in the Latent Image ROI. The common Base Set modeling yielded a Rarity prediction of 1 in 1,162,199,175,291. The base 10 logarithm of this Rarity is 12.0653 which gives the order of magnitude of the Rarity prediction. The following graphic is a plot of the Base 10 logarithm of the Rarity prediction vertically versus the number of minutia points matched between the Latent Image RPI and the reported ground truth mate image.

Log Base 10 Rarity v. Minutia



In the above plot, the order of magnitude of Rarity is succinctly expressed via the base 10 logarithm of the predicted Rarity. In the plot, the Rarity orders of magnitude tend to rise with the number of minutia; however, orders of magnitude vary within the ranges of 4 to 14 minutia. The WARP induced scoring of similarity captures Level 2 information significantly beyond minutia points. Further, holding the number of minutia constant, the quantity of Level 2 ridge information, in general, is likely to vary significantly across latent images. Without the kind of guidance provided by the methods of this Grant, an LPE must rely on subjective assessments of rarity of Level 2 similarity to a latent image.

Key results for the thirty Latent Images from the above plot are listed in the following Table.

Latents Fully Analyzed in the Grant

Latent	Median Observations for Analysis	Minutia	Remainder Percentage	GT Score	GT p-Value	Predicted Rarity	Log Base 10 of Rarity
B117	19,829	11	78	-7.01226	1.17E-12	852,912,259,109	11.93
B122	19,830	6	99	-4.65554	1.616E-6	618,926	5.79
B124	19,813	4	57	-4.39349	5.577E-6	179,295	5.25
B126	19,833	26	95	-8.44124	1.57E-17	63,694,444,445,493,800	16.80
B129	19,830	6	98	-1.93605	0.026431	37	1.57
B139	19,815	6	100	-5.26811	6.89E-8	14,509,698	7.16
B154	19,815	5	88	-5.11524	1.57E-7	6,382,703	6.81
B167	19,821	11	82	-6.84507	3.82E-12	261,641,392,900	11.42
B189	19,824	7	73	-4.45606	4.174E-6	239,582	5.38
B190	19,830	7	100	-5.11699	1.55E-7	6,442,390	6.81
B198	19,831	6	100	-4.15965	0.000015937	62,748	4.80
G012	19,823	9	100	-5.97732	1.13E-9	881,681,213	8.95
G073	19,827	19	70	-6.43406	6.21E-11	16,098,151,627	10.21
G087	19,824	12	100	-6.46668	5.01E-11	19,964,013,984	10.30
G095	19,831	12	78	-5.98839	1.06E-9	943,696,512	8.97
U202	19,816	4	100	-4.24494	0.000010933	91,468	4.96
U204	19,825	11	81	-6.73862	7.99E-12	125,079,736,825	11.10
U205	19,825	10	97	-7.61872	1.28E-14	78,064,662,183,219	13.89
U206	19,825	13	50	-6.04262	7.58E-10	1,318,974,409	9.12
U213	19,823	5	100	-5.21655	9.11E-8	10,971,549	7.04
U229	19,816	6	86	-5.78794	3.56E-9	280,682,634	8.45
U230	19,829	6	76	-5.25991	7.2E-8	13,877,093	7.14
U243	19,826	5	100	-3.21835	0.000644643	1,551	3.19
U246	19,546	4	88	-3.85782	0.000057201	17,482	4.24
U254	19,813	4	97	-3.99161	0.000032814	30,475	4.48
U260A	18,753	7	80	-7.05537	8.61E-13	1,161,864,294,637	12.07
U260B	19,775	7	76	-7.13324	4.9E-13	2,040,100,558,257	12.31
U281	19,819	11	93	-5.40428	3.25E-8	30,736,135	7.49
U291	17,289	5	86	-4.56591	2.487E-6	402,148	5.60
WHORL	19,825	15	99	-6.56278	2.64E-11	37,867,719,679	10.58

U260A is the common Base Set analysis
U260B is the 'Best 50' Base Set analysis

The WARP algorithm is designed to generate the best possible overlay of the latent ROI onto a reference image. Consequently, the algorithm is necessarily robust to imperfect or partial ridge information in both the latent and reference images. The algorithm cannot meet this requirement and mimic LPE expertise to opine exclusionary ridge structure. Heavily weighting exclusionary ridge information in the algorithm would lead to incorrectly eliminating potential matching images from the informative modeling data. We acknowledge that the similarity scoring has possibly low sensitivity to some exclusionary information in non-mate images that might cause the model to give lower predicted rarity for the ground truth mate than its possible "true" rarity. In particular, deltas have clusters of minutia in a small area. This presents messy information to the warp algorithm that might allow messy non-matching deltas to spuriously match Level 2 information while not penalizing scores for exclusionary superfluous information. These issues, if they exist, would make the predicted rarity of a ground truth mate more conservative. U206, for example, has a huge swath of open ridge structure and a delta, all of which match closely. It could be that close non-mate competitors have minutia that are not in the latent, but these minutia are not penalizing the similarity scoring appropriately.

B126 was an exception to our stated criterion for selection of latents for analysis which is that the matching information presented a challenging assessment for the LPE. A preponderance of minutia points, as seen in B126, is an indicator of a preponderance of unique Level 2 ridge structure that would imply rarity. B126 is a good image with 26 matching minutia and a base 10 logarithm of rarity of 16.8 that certainly constitutes a *leap of faith* decision level.

It is interesting that U205 has a predicted rarity of 1 in 78 trillion (and a base 10 logarithm of rarity of 13.89) with only ten minutia that are quite spread apart.

We will be pursuing collaboration with LPEs to examine the details related to analyzed latents and to build a detailed understanding of the relationship between specific image characteristics and rarity predictions. These collaborations would include the examination of non-mates with the high similarity to the latent.

Participants & Other Collaborating Organizations

Grant PI: Donald T. Gantz, PhD, Professor Emeritus of Statistics, The Volgenau School of Engineering, George Mason University

Grant Co-PI: JohnJ. Miller, PhD, Associate Professor Emeritus, The Volgenau School of Engineering, George Mason University

Grant Subawardee: Sciometrics LLC, 14150 Parkeast Circle, Chantilly, Virginia 20151

The Grant researchers have collaborated with Sciometrics and Latent Fingerprint Examiners from the Virginia Department of Forensic Science (VADFS) during the Grant research. Sciometrics, as a Grant subawardee, augmented its LatentSleuth software with the computational algorithms required to produce the research data. The VADFS has been using LatentSleuth on casework since March 2019. Their accreditation of LatentSleuth on casework followed a 2 year NIJ Grant supported study of LatentSleuth's accuracy and effectiveness. The VADFS LPEs were a valuable resource for the current Grant researchers. Collaboration with Sciometrics and the VADFS LPEs included joint presentations at the Chesapeake Bay Division of the International Association for Identification (CBDIAI) annual Spring Conference and Fall Seminar in 2019. Further collaborative research and publication options are under consideration.

Outcomes

The Grant research introduces a notion of a data base RMP that is computed automatically using an Objective Measure of Level 2 Similarity to the Latent Image ROI. When computed for a Reference Image for which the LPE has found no exclusionary information, the predicted data base RMP for the Reference Image provides an objective basis for the LPE report.

Computations of the Objective Measure of Similarity for all examples in this Report were done within LatentSleuth, a commercially available workstation for Latent Fingerprint Examination. A common 50 image Base Set and a common 20,000 image randomly selected Reference Set were used to compute the predicted data base RMP for all examples. The predicted data base RMP remained the same for those latents for which an additional modelling was done using the same Base Set but using a different randomly selected set of 20,000 known non-mates from the same large data base.

The Grant 's use of a commercially available workstation, common Base and Reference Sets, and transparent computational algorithms support the feasibility of exporting a standard modeling capability to the LPE community. Further, any technology capable of computing a Level 2 error measurement at all locations in the Latent Image can utilize all other components of the process. The LatentSleuth WARP is such a technology. The LatentSleuth WARP is very accurate in locating the best fit of the Latent Image ROI Level 2 structure within any Reference Image while accounting for distortion across the fit. This allows all Reference images to compete (with a Base Set of images) for Level 2 correspondence with the Latent Image ROI across the entire Latent Image ROI. **The foundation for the predictive model of similarity is the Reference data base's ability to cover the Level 2 structure of the Latent Image ROI.**

The modeling procedure makes no prior statistical assumptions upon which to base the statistical model of similarity to a latent. Rather, the data analysis algorithm used to model RMP prediction is shown to demonstrate reliably close normal distribution properties so that it is reasonable to use a normal distribution for prediction.

The Grant has addressed important issues raised in *Strengthening Forensic Science in the United States: A Path Forward*. First, that Report states that, “the assessment of latent prints from crime scenes is based largely on human interpretation.” The Report further states, “Clearly, the reliability of the ACE-V process could be improved if specific measurement criteria were defined.” The proposed Research Project has introduced an objective measure of similarity between a Latent Image and an exemplar requiring no minutiae markup.

The goal of the research project has been to put a firm theoretical foundation to the quantification of the degree of similarity that a reference image has to a latent image. By providing latent fingerprint examiners with an objective measure of similarity between an exemplar image and a latent together with an associated statistical random match error statement, the research in this Grant is taking a significant step towards putting latent fingerprint examination on a scientific base.

The data generation requirement of this research, in itself, has demonstrated that it is feasible to ‘*enroll*’ a latent image through its automated WARPing to few known non-mate fingerprints yielding a model that is the basis for computing similarity to the latent for any candidate image. This capability alone should have a very significant impact on the utilization of latent images by criminal justice professionals. For instance, this capability should allow professionals much more conveniently to ‘connect the dots’ between crimes and persons of interest. The current labor intensity of latent fingerprint identification and the associated requirements for latent image quality combine to underutilize latent images. This summarizes a potentially significant implicit impact that this research could bring to the use of latent images for investigation.