

**Statistical Models for the Support
of Forensic Fingerprint
Identifications**

by

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CERTIFICATE OF ORIGINAL AUTHORSHIP

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List of Publications and Presentations

Peer-Reviewed Papers

1. Abraham, J., Champod, C., Lennard, C. and Roux, C. (2013). Spatial analysis of corresponding fingerprint features from match and close non-match populations. *Forensic Sci. Int. vol. 230 no. 13*, pp. 87-98.
2. Abraham, J., Champod, C., Lennard, C. and Roux, C. (2013). Modern statistical models for forensic fingerprint examinations: A critical review. *Forensic Sci. Int. vol. 232 no. 13*, pp. 131-150.

Book Chapters

1. Abraham, J., Champod, C., Lennard, C. and Roux, C. (2013). An AFIS Candidate List Centric Fingerprint Likelihood Ratio Model based on Morphometric and Spatial Analyses (MSA), *New Trends and Developments in Biometrics, Jucheng Yang and Shan Juan Xie (eds.), ISBN: 978-953-51-0859-7, InTech*.

Conference Presentations

1. A Practical Statistical Model for Fingerprint Comparisons. *The 23rd International Symposium on the Forensic Sciences (ANZFSS 2016), Auckland, 2016*.
2. Calculating Likelihood Ratios for Fingerprint Identification ‘Cold hit’ and ‘Warm Hit’ Cases. *The International Fingerprint Research Group Conference, Patiala, India, 2015*.
3. Modelling the Variability of Minutiae using Machine Learning and Statistical Analysis to Calculate Likelihood Ratios for ‘Warm Hit’ Cases. *The 22nd International Symposium on the Forensic Sciences (ANZFSS 2014), Adelaide, 2014*.
4. Spatial Analysis of Corresponding Fingerprint Features from Match and Close Non-Match Populations. *The 6th European Academy of Forensic Science Conference, The Hague, 2012*.

5. Spatial Analysis of Corresponding Fingerprint Features from Match and Close Non-Match Populations. *The 21st International Symposium on the Forensic Sciences (ANZFSS 2012), Hobart, 2012.*

Abstract

For the majority of the 20th century, the forensic practice of fingerprint identification has had unanimous acceptance as reliable, robust, and admissible evidence. However, a number of forensic commentators have questioned the scientific validity of the current practice of fingerprint identification. Moreover, recent well publicised misidentifications have added concerns with the accuracy and quality assurance processes in practice, while fingerprint practitioners have experienced growing pressure to perform identifications from increasing workload and difficult casework.

The application of statistical modelling for fingerprint identification is a scientific methodology that provides a quantification of fingerprint evidence that can alleviate such concerns regarding the scientific foundations of fingerprint identification. Moreover, such statistical models can be used as a supportive tool for fingerprint practitioners who are under operational pressure to accurately assess crime marks against other fingermarks in a timely manner.

In this dissertation, two statistical modelling frameworks for different fingerprint identification scenarios are proposed. The first variant is called AFIS-centric models that calculate likelihood ratios and are designed to work with AFIS candidate lists, helping the practitioner to decide between match and close non-match correspondences. Two likelihood ratio measures are proposed, one with the aim of evaluating candidate list members as match or a close non-match, the other providing a weight-of-evidence evaluation.

The second model variant called a Person-of-Interest (POI) model is designed for the scenario where a rich collection of fingermarks from the same source finger are available to provide a more thorough evidential assessment. Tailored models of skin distortion are built using samples of the POI's finger, using feature vectors that make use of all of the available spatial information, from which a weight-of-evidence likelihood ratio measure is derived.

Experimental results illustrate the effectiveness of the AFIS-centric and POI models as supportive tools for casework. The significance of these research results is threefold. Firstly, the proposed AFIS-centric models illustrate how feature vector based models can focus on match and close non-match populations to provide a statistical measure agnostic of an AFIS scores that can be used for workload reduction purposes through candidate list filtering/reordering and quality assurance within the Analysis-Comparison-Evaluation-Verification (ACE-V) framework. Secondly, the proposed feature vectors add robustness and spatial completeness to the model, resulting in highly accurate models that assess real-world case samples accurately. Lastly, both proposed model variants provide a highly robust and accurate quantitative output in the form of a weight-of-evidence measure that can be used to support expert testimony.