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TECHNICAL NOTE

CRIMINALISTICS

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Empirical Evaluation of the Reliability of Photogrammetry Software in the Recovery of Three-Dimensional Footwear Impressions*

ABSTRACT: This paper examines the reliability of Structure from Motion (SfM) photogrammetry as a tool in the capture of forensic footwear marks. This is applicable to photogrammetry freeware DigTrace but is equally relevant to other SfM solutions. SfM simply requires a digital camera, a scale bar, and a selection of oblique photographs of the trace in question taken at the scene. The output is a digital three-dimensional point cloud of the surface and any plastic trace thereon. The first section of this paper examines the reliability of photogrammetry to capture the same data when repeatedly used on one impression, while the second part assesses the impact of varying cameras. Using cloud to cloud comparisons that measure the distance between two-point clouds, we assess the variability between models. The results highlight how little variability is evident and therefore speak to the accuracy and consistency of such techniques in the capture of three-dimensional traces. Using this method, 3D footwear impressions can, in many substrates, be collected with a repeatability of 97% with any variation between models less than ~0.5 mm.

KEYWORDS: evidence recovery, footwear impression, three-dimensional, 3D, digital evidence, reliability testing, validity

Footwear evidence relies upon human pattern-matching, analysis of those matches and ultimately the opinion of the examiner. Consequently, it has been criticized in the past for a lack of scientific objectivity. U.S. and U.K. Government reports have called over the last decade for the increasing use of more objective, preferably automated techniques, that have a proven level of accuracy and precision (1,2). An increasing amount of research is now focused on demonstrating the limits of accuracy and precision of a given technique, or piece of forensic equipment. This focus on reliability and quantification of error margins is not new. For example, "The Frye Standard," introduced in 1923 required evidence to have a "general level of acceptance in the specific scientific community to be admissible in court" (3). This was followed by a 1993 US Appeal court ruling known as the Daubert standard. This broadened the admissibility test for evidence, but also challenged the use of scientifically unchallenged expert witness statements (4). This liberal approach allowed for additional factors to affect the decision of admissibility. Neither set of rulings settled the matter definitively about what is, and is not, eligible in the way of scientific evidence and concerns remained (5). Forensic examiners and expert witnesses must strive, as they do always, to improve the reliability of the raw data (evidence) collected at the scene and this is fundamental to addressing these types of concerns. While often neglected in favor of other lines of forensic data, the analysis of footwear marks is undergoing a minor revolution in terms of potential scene capture methods. This revolves around the application of small-scale (close-up) photogrammetry to capture 3D models, allowing rapid capture, visualization and numerical analysis of 3D traces. Footwear marks and impressions can now be recovered from a variety of locations and mediums without recourse to traditional casting or lifting methods. With the introduction of new techniques, it is essential that their reliability is examined and the sources of error or variance established. The aim of this paper is to provide an assessment of the reliability and reproducibility of small-scale 3D capture methods involving structure from motion (SfM) photogrammetry.

Reliability has previously been defined as a combination of repeatability, reproducibility, and accuracy (6) a definition that draws from the PCAST definition (6).

Andalo et al. (7) demonstrate the potential of SfM in the recovery of footwear evidence and through the advent of freeware such as DigTrace (8) this is now openly available to practitioners. In addition, commercial solutions such as that provided by Agisoft are also available and increasingly being marketed to forensic practitioners. Photogrammetry is successfully being used in other disciplines to capture and visualize in three-dimensional traces. Archaeological and geological uses are now common, whether to capture small finds or entire landscapes. All manner of camera types, drones, action video cameras are utilized to do so. Examples of this include Zimmer et al. (9) and Matthews et al (10). The use of photogrammetry in other areas of forensic practice highlight the perceived value and general feelings of the community regarding the technique; specifically regarding levels

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of accuracy and validity (11,12). Currently, three-dimensional footwear impressions are either cast or photographed in 2D. Casting has been used for over a century to collect the three-dimensional data of an impression but is not underpinned by a body of peer-reviewed research (13). With the advent of an alternative, we must gain a measure of the reliability in 3D capture methods. In light of this, we evaluate the reliability of Structure from Motion (SfM) photogrammetry in capturing footwear evidence.

Methods

There are two elements to the method used. Firstly, establishing a standard protocol for the capture of images for use with SfM algorithms and secondly, establishing a means of comparing 3D outputs.

Close Range Photogrammetry Procedure

Falkingham (14) alongside Bennett and Budka (8) provide several important methodological points regarding the use of open-source SfM photogrammetry. To make a model of a footwear impression, a standard photographic procedure, developed by the authors, is followed (Fig. 1). While some latitude is possible, the key elements must be adhered to. At least 20 sharp photographs from different angles around and above the impression are needed extending well beyond the immediate area of the subject. SfM works by matching individual, or groups of, pixels identified automatically between different images taken with different oblique orientations. This is used to place first the camera positions and then the pixels themselves in three-dimensional space via photogrammetry. In this way, the surface of the impression is depicted by a cloud of points each with an x, y, and z coordinate. This is then scaled in relation to a ruler or scale bar placed by the impression prior to the photographs being taken. The surface of the point cloud can then be meshed using a variety of alternative surfacing algorithms (8). While the principles remain constant across different SfM algorithms and workflows, the details vary.

TABLE 1—*Cloud to cloud comparison statistics to show variation between models of the same impression in sand (selected at random from pot of 50).*

Model 1	Model 2	Mean Distance (mm)	Std Deviation	RMS	Distance Between Points (mm) of 99% of Model	Distance Between Points (mm) of 90% of Model
42	6	0.235	0.157	0.595	0.815	0.430
15	41	0.168	0.082	0.578	0.432	0.263
37	39	0.161	0.089	0.556	0.475	0.254
44	13	0.176	0.084	0.552	0.446	0.279
38	35	0.174	0.088	0.563	0.474	0.276
49	30	0.204	0.120	0.689	0.609	0.333
48	14	0.197	0.096	0.600	0.478	0.320
1	25	0.265	0.152	0.610	0.735	0.465
43	50	0.176	0.093	0.568	0.502	0.281
23	26	0.202	0.110	0.675	0.564	0.341
7	14	0.231	0.141	0.600	0.699	0.408
34	46	0.171	0.092	0.564	0.475	0.274
9	44	0.216	0.126	0.576	0.608	0.358
39	41	0.169	0.087	0.554	0.454	0.261
45	50	0.194	0.129	0.562	0.690	0.308
38	6	0.255	0.180	0.608	0.970	0.467
37	4	0.346	0.209	0.670	1.045	0.602
47	22	0.169	0.093	0.566	0.499	0.267
30	2	0.293	0.179	0.613	0.948	0.496
28	42	0.199	0.114	0.581	0.603	0.326
Average		0.210	0.121	0.594	0.626	0.350

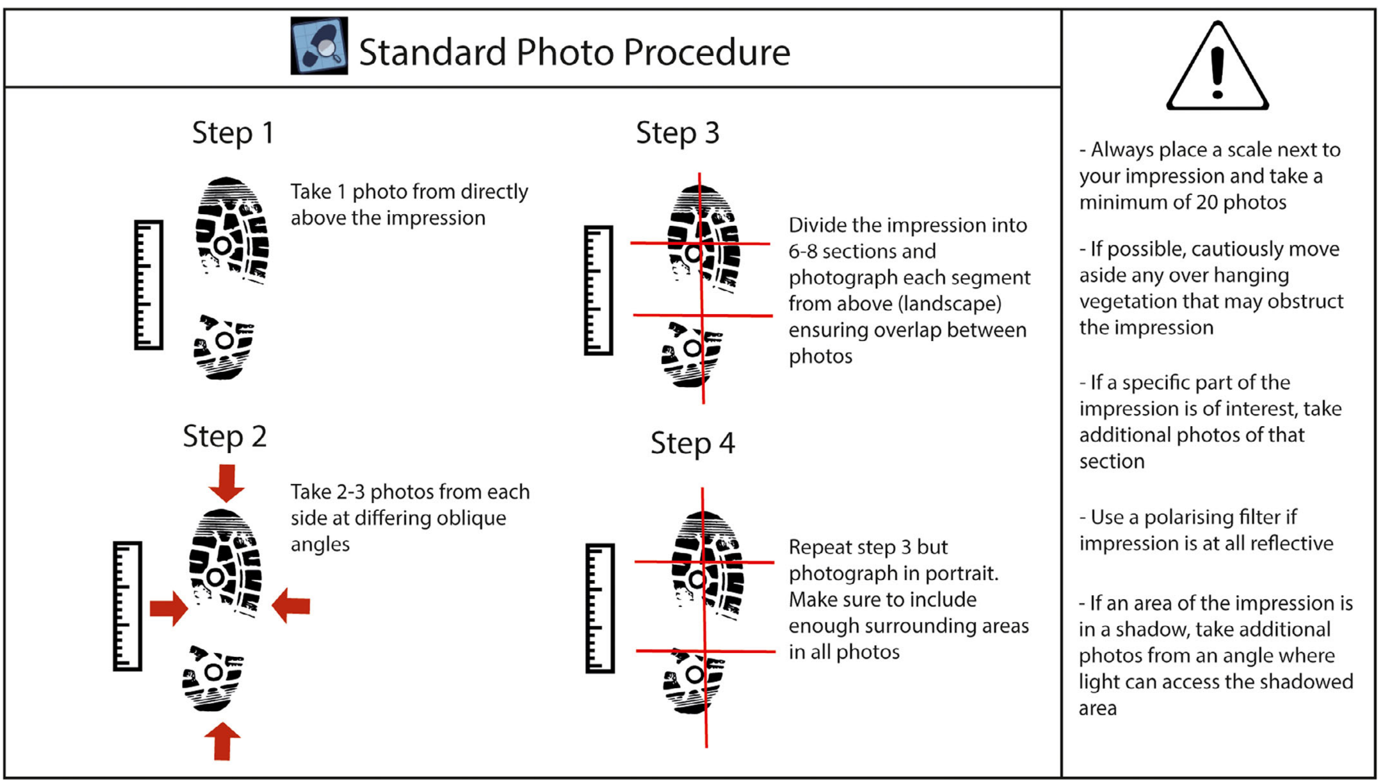

FIG. 1—*Author's photo procedure for use with DigTrace.*

Unlike commercial photogrammetry solutions, DigTrace was developed specifically for the capture and analysis of footwear and fossil footprint impressions and uses open-source code for the SfM process (OpenMVG) (15). The output is an x, y, and z file saved in an asc, csv, or ply. format and analyzed within DigTrace as required or exported to other software solutions.

There are several potential areas of error associated with SfM beyond the failure of the algorithms used to match points

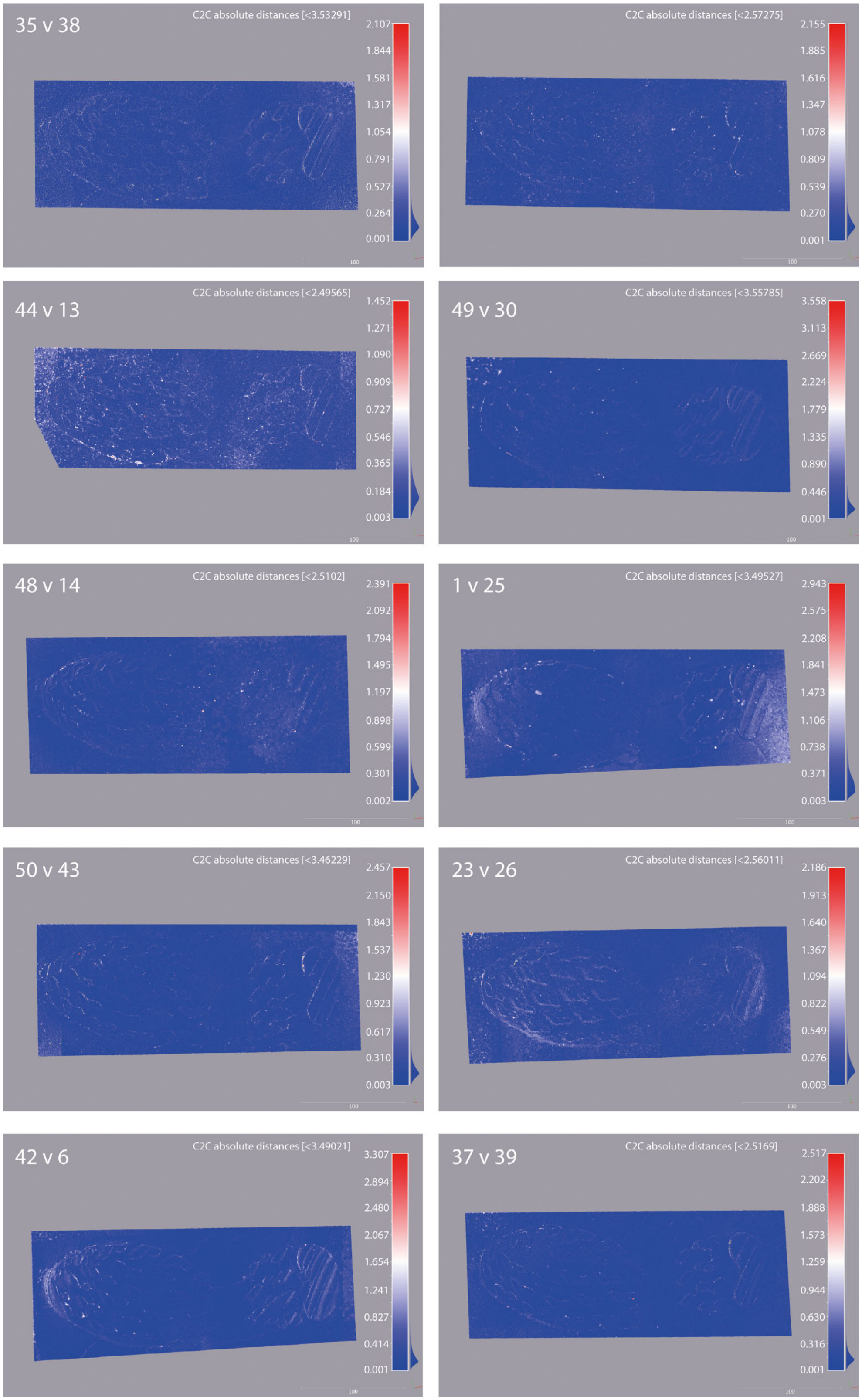

FIG. 2—*Example Cloud to Cloud distance heat maps of 10 randomly selected cloud pairs for models made of a shoeprint in sand. Scale in mm.*

successfully that may occur where surfaces have little or no pixel contrast (i.e., are to uniform) or are reflective leading to false placement of points. Here we focus on the user-controlled errors, these are linked to: (i) variance between point clouds created of the same subject but with different combinations of photographs; and (ii) the impact of changing different cameras depending on what is available to a scene officer at a given moment. Included in the first of these errors is the issue of scaling a model using the ruler or scale bar.

A sand impression was used as the subject in the first part of this experiment, placed outdoor in uniform light. The procedure outlined in Fig. 1 was used to collect photographs for 50 three-dimensional models. Between each set of photographs, the operator straightened-up, put the camera down and looked away. Each of the 50 sets of circa. Twenty images were then used to build 50 independent three-dimensional models of the subject using DigTrace. The precise orientation and frame of each picture in the 20–30 used to build each 3D model is different, this is the critical variable that is independent. This is equivalent to making 50 independent models. The models were numbered 1–50 and twenty pairs were selected at random for comparison. This process was repeated using impressions made in natural settings in both snow and mud. A second user was introduced to collect the snow photographs. In a second experiment four dental stone casts were used as the subject and two models of each were made with different cameras being used. Photographs were taken using a Full Frame Sony A7 mirrorless camera (24 megapixels) and an Apple Iphone XS Max (12 megapixels). Three-dimensional models were again made using DigTrace.

Cloud Comparisons

There are several methods available to compare point clouds and meshes. These range from simple comparison of least squares to more sophisticated measures such as Hausdorff Distances. They all give very similar results when dealing with 2D surfaces (8), and we have adopted that which can be easily implemented via CC or Meshlab and is increasingly an industry standard in object matching. Hausdorff distances are commonly used and can be seen to outperform other methods, with specific advantages such as not requiring user defined parameters identified (16). Here, however, we use the freeware CloudCompare (http://www.danielgm.net/cc/) to compute cloud to cloud distances. This method is similar to that of Thompson and Norris (17) and has been specifically used to compare the quality of experimental footprint surfaces by Wiseman (18) To ensure repeatability of this work, we document the method used in some detail, this would allow other users to repeat this experiment for their given equipment and/or software.

- Step One: Two different point clouds are imported into CloudCompare and aligned both in the x-y and z planes. A rough alignment was first undertaken using a system of matching points and with a minimum of 10 points being used in each case evenly distributed across the whole surface (i.e., including toe area, mid area, and heel area of model). This is simply a matter of matching identifiable landmark features on both point clouds. A fine alignment using an iterative closest point (ICP) algorithm was then applied. This minimized the difference between the two clouds to a root mean square of around 0.6.
- Step Two: Approximate cloud to cloud distances were then measured, this computes the distances between adjacent points on the two clouds using a "nearest neighbour" method. The first output is an option that reduces the maximum distance between the points reducing computational drain. Since the distances are low, the maximum distance is selected, and the process run again. The results are shown in a scalar color field and the standard deviation and mean of the distances reported.

Results

Using the tracks made in sand the randomly selected cloud pairs show little difference, with an average distance between points in any two clouds of 0.21 mm and a standard error of ±0.01mm (Table 1; Fig. 2). The more uniform the color in Fig. 2 (blue = 0 to <0.5 mm) the closer the two clouds map one to the other. There is less than 3% difference between the models compared (Table 1). In general, 99% of points have an inter-point distance of less than or equal to 0.626 mm. The patterns of errors are not focused on any one part of the impression although there is a concentration in some comparisons at the tip of the heel and toes (Fig. 2). In snow, 99% of points have an inter-point error of less than or equal to 3.123 mm, although the average error is only 0.542 mm with a standard error of ±0.016 mm. As with traditional casting, snow can be challenging for SfM capture due to reflection and the uniformity of the pixels. SfM performs best where there is lots of pixel color variability allowing features to be extracted easily; fresh snow can be a little uniform in color. A consequence is that SfM models of snow can have a greater number of holes, caused by missing points, compared to models made on other substrates. These small holes and imperfections result in the lower reliability values obtained (Table 2). The mud comparisons for randomly selected cloud pairs show results closer to sand with an average point to point distance between clouds of 0.248mm with a standard error of ±0.01mm (Table 3). A histogram example of a

TABLE 2—*Cloud to cloud comparison statistics to show variation between models of the same impression in snow (selected at random from pot of 50).*

Model 1	Model 2	Mean Distance (mm)	Std Deviation	RMS	Distance Between Points (mm) of 99% of Model	Distance Between Points (mm) of 90% of Model
15	5	0.574	0.745	0.943	3.465	0.935
39	8	0.524	0.520	0.924	2.793	0.908
45	43	0.478	0.474	0.875	2.440	0.812
4	32	0.516	0.629	0.877	3.697	0.902
19	38	0.571	0.601	0.969	3.365	1.047
46	47	0.537	0.562	0.843	2.698	0.271
31	33	0.628	0.649	1.182	2.782	1.065
16	41	0.550	0.684	0.890	3.668	0.940
28	18	0.492	0.448	0.923	2.158	0.846
2	35	0.654	0.996	1.085	5.441	1.055
16	17	0.494	0.550	0.785	2.975	0.848
21	34	0.568	0.565	0.967	2.909	1.067
48	32	0.519	0.532	0.937	2.515	0.902
35	46	0.497	0.525	0.775	2.702	0.817
20	47	0.732	0.682	1.708	3.805	1.234
1	14	0.548	0.958	0.849	4.565	0.790
6	38	0.544	0.639	0.916	3.279	0.945
19	14	0.385	0.376	0.801	1.690	0.684
39	30	0.558	0.971	0.887	3.021	0.896
46	44	0.477	0.559	0.759	2.486	0.764
Average		0.542	0.633	0.945	3.123	0.886

TABLE 3—*Cloud to cloud comparison statistics to show variation between models of the same impression in mud (selected at random from pot of 50).*

Model 1	Model 2	Mean Distance (mm)	Std Deviation	RMS	Distance Between Points (mm) of 99% of Model	Distance Between Points (mm) of 90% of Model
42	35	0.232	0.157	0.705	0.783	0.404
2	11	0.252	0.222	0.504	1.044	0.436
28	41	0.244	0.336	0.517	0.917	0.405
34	33	0.216	0.298	0.489	0.750	0.346
36	5	0.256	0.269	0.568	1.423	0.435
31	29	0.302	0.251	0.638	1.178	0.569
44	32	0.286	0.238	0.664	1.241	0.533
45	46	0.209	0.137	0.509	0.707	0.357
21	16	0.209	0.148	0.492	0.710	0.353
24	3	0.280	0.328	0.586	1.891	0.469
40	22	0.218	0.172	0.501	0.875	0.365
46	20	0.218	0.172	0.485	0.858	0.371
29	6	0.185	0.242	0.457	0.668	0.284
36	37	0.232	0.163	0.552	0.812	0.402
17	13	0.295	0.249	0.710	1.264	0.568
31	43	0.386	0.411	0.734	1.796	0.771
6	27	0.242	0.249	0.500	1.121	0.413
41	20	0.209	0.267	0.507	0.816	0.331
40	45	0.225	0.294	0.503	0.873	0.356
12	15	0.260	0.230	0.614	1.173	0.462
Average		0.248	0.242	0.562	1.045	0.432

mud paired model comparison is shown in Fig. 3, illustrating the frequency of point cloud distances with the vast majority of points being between 0 and 0.5 mm.

In terms of the second experiment using different cameras the cloud to cloud comparisons are shown in Fig. 4. One of the cameras was a smartphone (Iphone XS) the other a full frame mirrorless camera (Sony A7). In this case, the difference between the computed point clouds is low. Of the four comparisons completed the mean point distance was of the order of as little as ~0.193 mm (Table 4). A difference this low provides a level of confidence that, regardless of the camera used, the three-dimensional model will be close to being identical.

Discussion

Cloud to cloud distances from multiple models of the same impression demonstrate the reliability of a SfM type approach for a given trace environment. Photogrammetry of this kind relies upon input photographs from different angles and heights, which will vary from occasion to occasion and from operator to operator hence the importance of establishing this type of reliability assessment. For DigTrace or similar programmes to be used as a forensic tool, we need to be able to say with certainty that the results of each model would be the same if the process were to be repeated by the same user or a different one.

The results of the reliability test show which substrates tested would only require one model of the impression to accurately reproduce the impression as evidence. It is intended for this method to be repeated by other examiners in order to create a library of repeatability and reproducibility rates in all manner of substrates. The results differ slightly with environment as each environment may have attributes that lend themselves to SfM more than others. Snow can be seen in this experiment to have the largest disparity between clouds as it incorporates the larger distances that model holes create. This highlights that additional steps in the recovery methodology may be required to increase the reliability, by increasing the quality of the models. This includes the application of contrast increasing sprays or controlling the light sources around the impression. The disparity between the snow results and the sand and mud results could be attributed to being taken by another user but, under inspection of

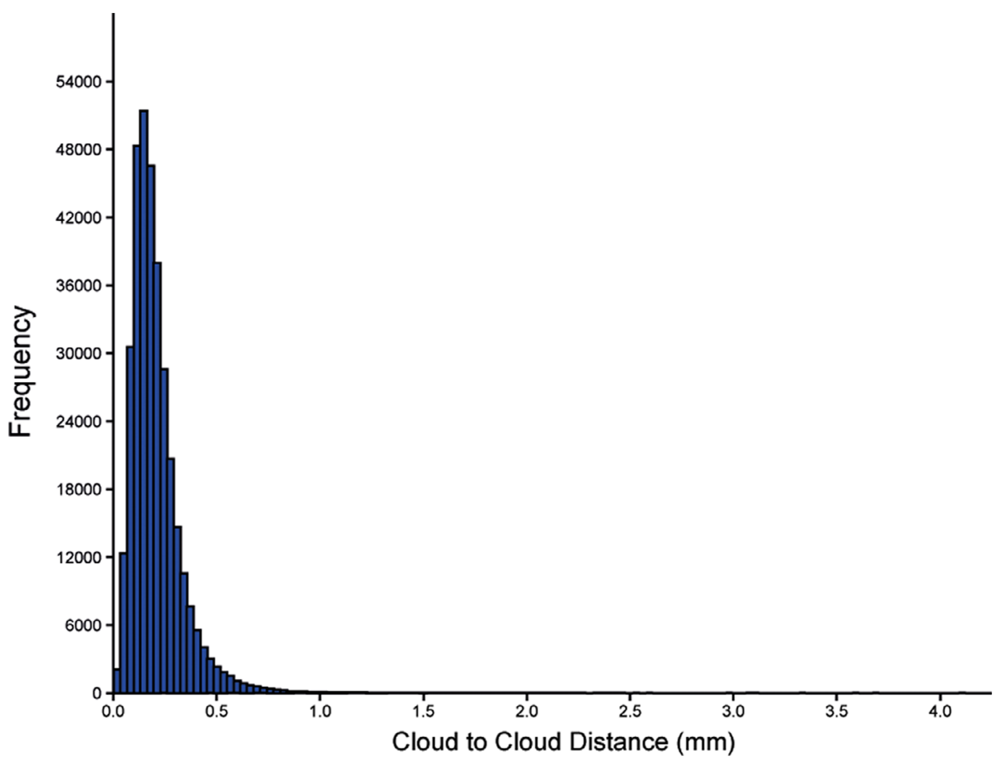

FIG. 3—*Example histogram of Model 16 and Model 21 mud comparison.*

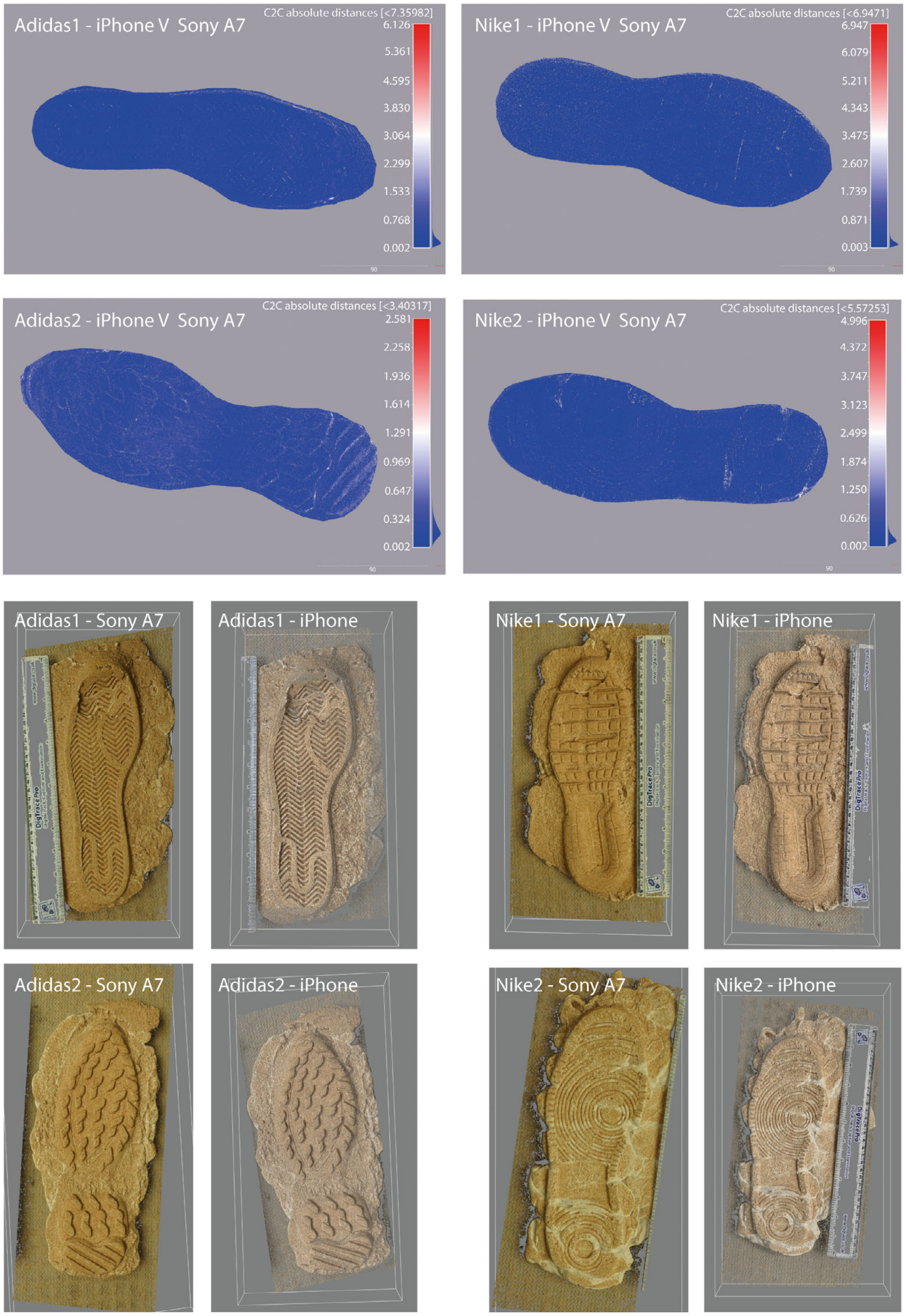

FIG. 4—*Cloud comparisons of camera type in scalar field format. Followed by initial DigTrace models.*

the photographs, the author deemed them to be of sufficient quality and in alignment with the photographic procedure. The sand experiment undertaken in this paper illustrates as near to perfect conditions as possible, thus giving us a confidence level of the method. The snow and mud experiments were conducted in more realistic conditions and allow a greater understanding of the entire method in different environments. The average error rate for snow at 99% is 3.123 mm. This is significant in relation to footwear where shoe sizes fall into a size category based on a matter of millimeters. Erroneous conclusions could, however, be mitigated to a certain degree by visual analysis of the point cloud. The output as seen in Fig. 2 identifies the area of the impression that shows largest disparity. The high error rating could, therefore, be successfully attributed to a certain area allowing for confident conclusions regarding the rest of the impression to be made.

The technique described, although robust, does rely upon a user collecting appropriate photographs of an impression as per Fig. 1. Poor understanding of the instructions could lead to poor models and this should also be considered at a training level.

TABLE 4—*Cloud to cloud statistics detailing the variability in point clouds when using an iphone and a Sony A7 to acquire photographs.*

Model 1	Model 2	Mean Distance	Std Deviation	RMS	Distance Between Points (mm) of ~97% of Model
Adidas (1) iPhone	Adidas (1) Sony A7	0.205	0.137	0.570	<0.505
Adidas (2) iPhone	Adidas (2) Sony A7	0.213	0.109	0.539	<0.455
Nike (1) iPhone	Nike (1) Sony A7	0.163	0.089	0.561	<0.355
Nike (2) iPhone	Nike (2) Sony A7	0.190	0.121	0.564	<0.411
Average		0.193	0.114		0.432

However, this will manifest itself in models that have missing parts or large holes and careful examination of a point cloud is essential to mitigate this. It is worth noting that commercial SfM algorithms such as those provided by Agisoft have a workflow that automatically provides a surface or mesh between the points. This is a natural hole filling profile, and it is essential that in all cases the original point clouds, that is the raw data, is examined and that surfaced models are not accepted without question.

The second experiment is important particularly given the increasing ubiquity of smartphones with high quality cameras. The smartphone model gave results comparable to a high quality forensic grade camera. Having said this, the results confirm that the better the image taken the better, within reason, the output model. There are areas of slightly higher inter-cloud distances in the Adidas 1 and Nike 2 comparisons (lower right corners Fig. 4). These can be attributed to the smartphone models not having enough photos of this area at different oblique angles, which could be addressed by increasing the number of photographs collected via a smartphone as default. Other differences reflect the fact that the mirrorless camera manual settings were used to ensure the highest quality photographs were obtained varying the aperture, shutter speed, white balance, exposure, and ISO. These settings are all automatic on the smartphone. The differences noted here are superficial and as per the cloud to cloud comparisons results, the variability between the clouds is low.

One of the transformative powers of SfM for the capture of trace evidence is the use of the smartphone which has the advantages of availability, speed, and ease of collection. The potential to develop solutions that aim to provide real-time intelligence from trace evidence is clear. The first attending officers could potentially collect evidence that is at risk of degradation, without waiting for crime scene examiners to attend.

It is also possible for a scene or forensic officer to calibrate their camera or smartphone and/or the typical environments that they face using the methods outlined here. This provides a means of officers addressing directly the fundamental question often posed in court or during accreditation process of "how reliable is your technique, equipment, and officers?"

The application of photogrammetry via SfM tools such as DigTrace can be considered a viable alternative, or least addition, to the recovery of three-dimensional impressions via traditional casting. Digital recovery of 3D impressions comes with many benefits, most notable are, calibration of the process, scale placement issues not existing as they do in 2D photographs, and lens distortion corrected for in the making of the 3D image. The photogrammetry process at scene requires a matter of minutes per impression. It is, therefore, much quicker than the traditional method of casting which requires time for mixing the product, pouring, setting, removing, and packaging the cast. The reliability of casting cannot be assessed as SfM photogrammetry has been in this study due to being a destructive technique. The high level of reliability that SfM photogrammetry has displayed with respect to repeatability and input differences are of a level appropriate to forensic science. In the current study, comparing cameras of very different specifications showed that the type of camera used at a crime scene does not negatively affect the output. This is particularly relevant in crime scene recovery as between forces and countries, the camera used to collect crime scene photographs will vary due to differences in budgets, practicality, and resources.

The limitations surrounding this study include the participation of only two users; further study is encouraged increasing this number. The authors have, over many years of research using DigTrace, seen little disparity between models created by different users and any differences that are seen are attributed to number and quality of photographs taken. Other variables could be further explored such as differences seen in DSLR cameras typically used for crime scene photography. The variability that exists in types of snow should also be a consideration for further research and reliability testing to avoid any erroneous conclusions being made.

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