INTERNATIONAL CONFERENCE ON ENGINEERING DESIGN, ICED23
24-28 JULY 2023, BORDEAUX, FRANCE

HOW DO PROTOTYPES CHANGE? CHARACTERISING QUANTITATIVE AND QUALITATIVE CHANGES BETWEEN PROTOTYPE ITERATIONS

Real, Ricardo;
Snider, Chris;
Goudswaard, Mark;
Hicks, Ben

University of Bristol

ABSTRACT

Prototyping strategies and technology often focus on reducing the fabrication time and cost between design iterations, however, there is limited knowledge about the specific characteristics of change that prototyping strategies aim to impact. To investigate, and better understand these characteristics, this study curates and systematically analyses a representative dataset of 50 'real-world' prototype samples. The study aims to explore the various elements that constitute a design change and to determine their impact on the scale of volumetric change detected. The results highlight emergent patterns and correlations between study metrics to better understand the reasons for design change and the frequency and scale of changes detected in the sample dataset. Findings reveal that the purpose of a design change is, in certain cases, highly correlated to the scale of change affected, and that some changes are more prevalent in the dataset than others, with an average volumetric difference of 4.2% between sample versions detected. The study provides an initial characterisation of prototype change to guide iterative prototyping processes and improve the efficiency and effectiveness of design iterations.

Keywords: Big data, Case study, Remanufacture, Change, Embodiment design

Contact:
Real, Ricardo
University of Bristol
United Kingdom
ric.real@bristol.ac.uk

Cite this article: Real, R., Snider, C., Goudswaard, M., Hicks, B. (2023) ‘How Do Prototypes Change? Characterising Quantitative and Qualitative Changes between Prototype Iterations’, in *Proceedings of the International Conference on Engineering Design (ICED23),* Bordeaux, France, 24-28 July 2023. DOI:10.1017/pds.2023.211

https://doi.org/10.1017/pds.2023.211 Published online by Cambridge University Press

1 INTRODUCTION

Prototyping is widely regarded an essential part of the New Product Development (NPD) process (Elverum et al., 2016) . Whether to explore novel concepts by building to think (Brown and Katz, 2011), or enhance an existing solution through refinement (Camburn et al., 2017), the prototype plays a crucial role in bridging the gap between an idea and its tangible form. Camere and Bordegoni (2016), describe prototyping as an engagement with the product to be, where the prototype approximates various features that constitute a final product, service, or system. Designers frequently manipulate the prototype in order to refine and enhance the final product through what Schon and Wiggins (1992) describe as a reflective conversation with the materials of the design solution. Organisations often prototype to embody new innovations (Schrage, 1996) with research showing that increased prototyping activity in the development stage leads to improved products (Camburn et al., 2017). However, where prototypes often go through several iterations in development, prototyping often predetermines a large portion of resource deployment, above all, time and cost (Camburn et al., 2017). In a landscape where speed to market is the key ingredient for competitiveness (Schrage, 1996), the speed of prototyping and subsequent testing become critical factors (Elverum et al., 2016). A study into the prototyping practices of design teams by (Yang, 2008) identifies that the percentage of time spent on fabrication is greater than that of other activities combined. And further, (Yang, 2008) observe a negative correlation between increased fabrication time and the resulting outcome. As such, recent works place focus on new methods to reduce fabrication time between prototype iterations. For example, (Real et al., 2022) investigates remanufacture as a method to cut time between prototype iterations, showing a significant potential reduction in fabrication time of up to 87%. Mathias et al. (2019), couples Additive Manufacture (AM) with LEGO in a hybrid process, reducing fabrication time by 45%. Whilst these works show promising results and give indication as to the direction in which prototyping strategies are tending, it is apparent that little is known about the characteristics of changes that such strategies are intended to affect. We know that prototypes change, however how they change with respect to both their physical and more subjective attributes is less clear. This study therefore aims to develop an initial characterisation of design changes by investigating the quantitative and qualitative properties of changes detected in a representative dataset of prototype samples. This work leverages the online ’thingiverse’ design repository to curate an arbitrary dataset of 50 ’real-world’ prototype samples. Samples comprise version 1 (V1) and modified version 2 (V2) design iterations which were analysed using computational methods to detect changes and generate a range of descriptive statistics. Datasets for the study were processed using ’IBM SPSS Statistics 27’ to identify emergent patterns and correlations between samples. Finally, the paper reflects on the implications of this work with relation to prototyping, limitations of the study, and opportunities for future work.

1.1 Aims

By better understanding how prototypes change, strategies for affecting change, such as remanufacture, can be better informed to align with the needs of prototyping in reducing iteration time and cost. This study aims to investigate the different elements that constitute a design change, and their influence on the scale of change identified. Where design changes often seem deceptively simple (Clarkson et al, 2004), fundamentally, this work looks to provide a steppingstone towards change characterisation, using a statistical approach to identify emergent patterns from a sample of prototype data to support the development of prototyping strategies and tools.

2 METHODOLOGY

In order to characterise change between prototype iterations a 3-stage methodology was adopted (Figure 1). The methodology allowed for a situated grounding of the study in the context of rapid prototyping, affording systematic evaluation to samples across quantitative and qualitative study metrics. Figure 1 details the methodological approach, from dataset curation to evaluation metric selection and description, before presenting the analysis method and subset of analysis datasets leading into results in Section 3.

https://doi.org/10.1017/pds.2023.211 Published online by Cambridge University Press

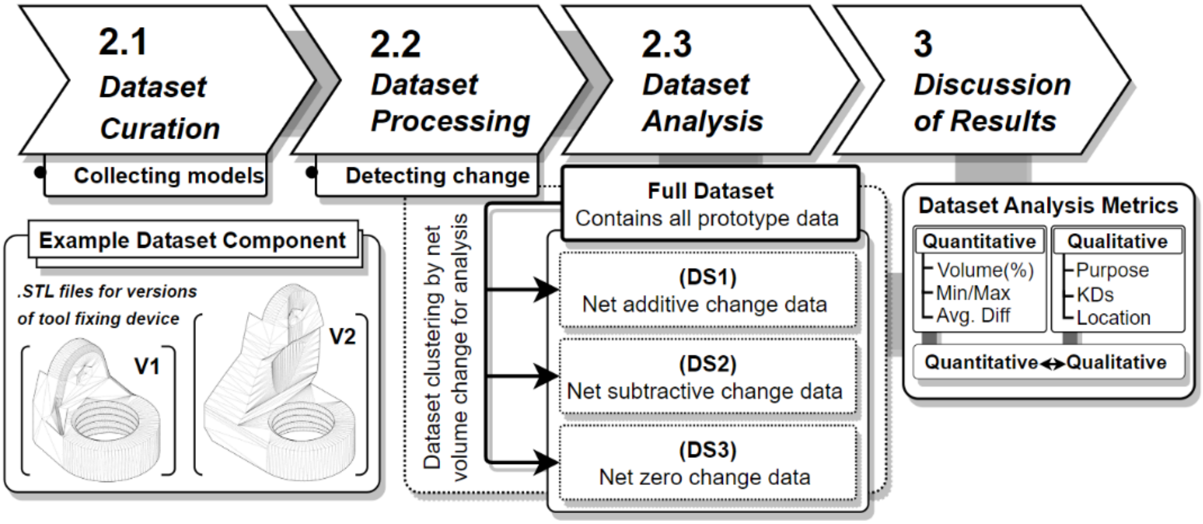

Figure 1. Study methodology used to detect and measure prototype changes.

2.1 Dataset curation

A dataset of 3D object files (.STL) was sampled from the'Thingiverse.com' digital model repository. The platform hosts over 2 million open-source 3D files uploaded by community members with the technical proficiency to design, document, and share object files (including revisions) of an original 'thing'. Between the 1st and 15th November 2022, the repository was queried using search terms '*V1, V2*' for projects containing multiple part versions in their documents, returning 4951 search results. From this pool, samples containing 'V1' and 'V2' files were randomly selected and vetted for damaged entries, generating a dataset of 50 samples, with 100 unique 3D object files.

Table 1. Dataset statistics V=Volume in mm^3, B=Bounding box (x,y,z) in mm.

Version	Qty	V.Min	B.Min	V.Max	B.Max	V.Avg	Std. Dev	Median
V1	50	1221	10,11,23	336741	156,156,80	47614	83000	11018
V2	50	1445	10,11,23	321376	156,156,80	46255	79127	12100

Table 1 provides an overview of the dataset statistics, featuring Min/Max part volumes(mm^3), and bounding box dimensions (x,y,z) for V1 and V2 files. All part files were found to fit in the build volume of a typical desktop FFF 3D printer. For reference the average part volume is similar to that of a compact computer mouse. It is assumed that part versions V1/V2 were created by the same user in each case and as such represent targeted refinements to the part, aiming to improve performance in some dimension of interest.

2.2 Dataset processing

To delineate a characterisation of change between versions, each of the 50 dataset samples were evaluated against a set of Quantitative and Qualitative metrics. The quantitative metrics were intended to capture the degrees of physical change between versions, whilst the qualitative metrics provide an indication of the rationale for a change, for instance adding functionality or refining the design through, for example, light-weighting. Measured values for each sample were logged and coded for database entry and analysis. Metrics are further discussed in the following section.

2.2.1 Measuring quantitative and qualitative change

Quantitative changes were detected following the computational analysis process outlined in prior works (Real et al., 2022). Component V1:V2 registrations were performed using an Iterative Closest Point Algorithm (ICP) from which the net volumetric percentage difference between versions was measured. Additionally, counts of the discrete changes per sample were taken, and the polarity of changes (added (+) or subtracted (-)) noted. Discrete changes determined to require material subtraction prior to any additive steps were further classified as 'Hybrid' and considered separately in the analysis.

https://doi.org/10.1017/pds.2023.211 Published online by Cambridge University Press

Qualitative evaluation metrics encompass aspects of change that are more subjective in interpretationand descriptive. In this study these are considered Location *v*(descriptive) i.e., where the change is implemented. Purpose i.e., an assumption as to the necessity of the change (Sanfilippo and Borgo, 2016; Townsend et al., 2011). And Dimension of change i.e., an assumption of the dimension in which knowledge has been developed to influence the change (Real et al., 2021). A coding schema to evaluate qualitative metrics was created (Table 2), and results were manually coded per sample by a researcher with prior experience in prototype evaluation, and KD coding studies (Real et al., 2021).

Table 2. Qualitative coding schema & evaluation metrics from prototyping literature.

Metric	Coding	Description
Location	Feature(**Fe**)	An entity of significance for a product lifecycle task, such as hole or pin Sanfilippo and Borgo (2016).
	Form(**Fo**)	Structural product characteristics that provide geometry through which functional features are delivered Townsend et al. (2011).
	Form & Feature(**F&F**)	Affecting both *Form* and *Feature*, i.e. a feature change resulting in a change to the surrounding form.
Purpose	Function(**F**)	Modifies the utilitarian aspect of the design, i.e. what it does Townsend et al. (2011).
	Refinement(**R**)	Gradual improvement to a design, i.e. feature optimisation, or tolerancing Camburn et al. (2017).
Dimension	Knowledge Dimensions (**KDs**)	Dimension in which knowledge is required to realise a change Real et al. (2021). (For brevity KD descriptions are given inline with results)

The metrics presented in Table 2 were extracted from the cited literature to define a set of measurable, and relatively unambiguous evaluation criteria for sample analysis. As readers may be less familiar with the KD coding schema of Real et al. (2021), this assessment metric is derived from Schon (1992) to determine the prototyping dimensions to which design knowledge is registered. For instance, a rearrangement of features might suggest an improved understanding of the design in the dimension of configuration.

2.3 Dataset analysis

Analysis was performed on four datasets, a global dataset (DS) containing all 50 samples, with further analysis performed on three subsidiary datasets. Subsidiary dataset samples were categorised by net volumetric difference, including Additive (DS1), where samples exhibit a net positive volumetric difference between versions. Subtractive (DS2) where the net sample difference is inversely negative, and Zero (DS3) where no, or negligible volumetric difference is detected. The data was analysed using descriptive statistics and exploratory analysis tools in 'IBM SPSS Statistics 27'.

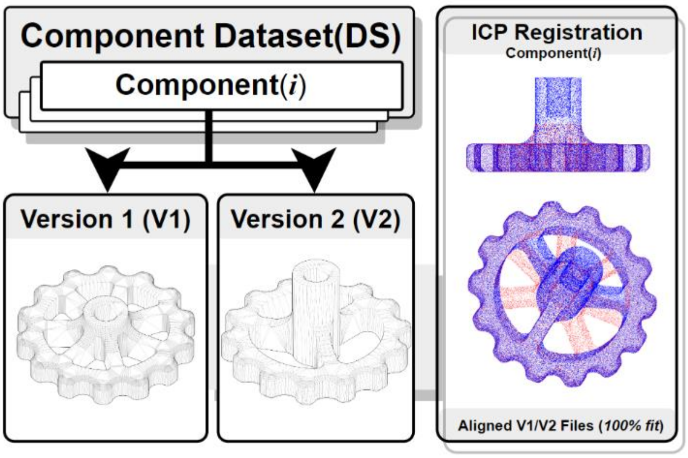

Figure 2. Example of a curated sample, ICP registration, and change detection.

https://doi.org/10.1017/pds.2023.211 Published online by Cambridge University Press

Figure 2 illustrates the study process, from dataset curation to registration and change detection. The sample shown is a 'FFF-Printer extruder knob' with two successive versions of its design.

3 RESULTS

Results are presented in three sections. The first reporting descriptive statistics from an analysis of quantitative component data. The second reporting qualitative data by means of frequency analysis. The third, investigates correlations between quantitative and qualitative data in relation to detected volumetric differences (%). For precision, section-wise results are organised by dataset, with results for the Complete (DS), and subsequent Additive (DS1), Subtractive (DS2), and where applicable, Zero (DS3) data subsets considered independently. Where sample size is comparatively small for DS3, key findings are presented at the end of the results section.

3.1 Quantitative results (descriptive dataset statistics)

Table 3 provides summary statistics for the complete sample dataset (DS) and the discrete changes identified (Δ Types). For DS, volumetric changes are measured within the range of -47.1% to 127.4%, with a mean change of 4.2% between sample versions. Respectively, mean change in the additive subset (DS1) was measured at 21.4%, and -10.1% for the subtractive (DS2) samples, suggesting that where an additive change is required, the scale of change is generally greater. Findings show the majority of samples exhibit a net subtractive change (23), marginally succeeding net additive (21), with a further (6) showing negligible difference between versions (<0.1 mm^3). Samples featuring a singular change are more prevalent in the DS dataset than samples with multiple changes, 74% of V2 designs comprise a singular change from their V1 counterpart. Overall, 75 discrete changes are detected in the DS dataset averaging 1.5 changes per sample. This supports the finding that there are few, between 1 and 2, distinctions between versions, reflecting that designers are typically focused on revisions and not broader changes. Subtractive and hybrid changes constitute the majority of discrete changes with 37.3%, and 34.7% of changes, respectively. Further analysis into the distribution of change volume (Figure 3.) shows the central tendency of volumetric difference in DS samples to be unimodal and clustered between -10% and 10% volume difference (Figure 3.1. a). Thus, suggesting the majority of changes to be small in relation to part volume. Examining DS1, and DS2 it is clear that a greater distribution of volumetric change is present in DS1 additive samples (Figure 3.1. c) where the only 2 cases above 100% are identified. For DS2 (Figure 3.1. b) variation in the distribution is less pronounced with a smaller Std.Dev of 14.1 to that of DS1's 35.5, suggesting subtractive changes to be characteristically smaller in scale. Investigating the quantity of changes per data sample (Figure 3.2), it is evident that the distribution is mostly uniform in each dataset. However, subtractive samples (DS2) are more frequently observed to contain more than one change between versions with 34.7% of DS2 samples, compared to 19% of DS1 (Figure 3.2).

Table 3. Sample descriptive statistics and change types (Δ) for DS TO DS3.

	DS	DS1	DS2	DS3
Samples(Cp)	**50**	**21**	**23**	**6**
Min(Δ)	-47.1%	0.3%	-0.1%	0%
Max(Δ)	127.4%	127.4%	-47.1%	0%
Avg(Δ)	4.2%	21.4%	-10.1%	0%
Std.Dev(Δ)	28.5	35.5	14.1	0
Singular	(37)	17	15	4
Multiple	(13)	4	8	2
ΔTypes	(75)	36	39	0
Additive	(21/75)	16	3	2
Subtractive	(28/75)	7	24	7
Hybrid	(26/75)	13	12	1
Avg(Δ/**Cp**)	1.5	1.71	1.7	1.3
Std.Dev(Δ/**Cp**)	1.26	1.82	1.7	0.4

3.2 Qualitative results (dataset frequency analysis)

Qualitative findings are proportionally illustrated by Figure 4, Counts are provided for the number of observations, and coding is kept consistent across datasets. Foremost, individual findings for each metric, Location (a.), Purpose (b.), and Dimension (c.) are presented, before discussing emergent correlations observed in the data. Findings for Location (a.) show the majority of changes to be located to a Feature (48%), followed by Form (40%), and relatively few changes (12%) spanning both Form and Feature. This suggests that changes are more frequently constrained to a specific location.

https://doi.org/10.1017/pds.2023.211 Published online by Cambridge University Press

For Purpose(b.) a large proportion of samples (64%) show Refinement to be the primary objective of change, with fewer, 36%, altering Function by way of iteration. Dimension (c.) shows Design Elements (features or components that comprise a design) are detected most frequently (42%), with Form (shape and size of the design), and Character (design aesthetic and styling) accounting for 28% and 14% of detected dimensions. Of interest, DS3 contributes the highest proportion of counts to the Character dimension (57%). Configuration (12%) and Manufacture (4%) are the KDs appearing least, with no other KDs detected in the sample. Little variation in the proportion of counts is observed across datasets, indicating that the polarity of change (additive/subtractive) is not correlated to its rationale. However, the influence of rationale on the scale of change is further investigated in section 3.3. **Qualitative data correlations:** there is an apparent degree of correlation between qualitative metrics (a. b. c.) in datasets DS through DS2. These findings infer that the most probable, or ’common change’ made between versions of a prototype is located to a feature, for the purpose of refinement, assuming a developed knowledge of its design elements.

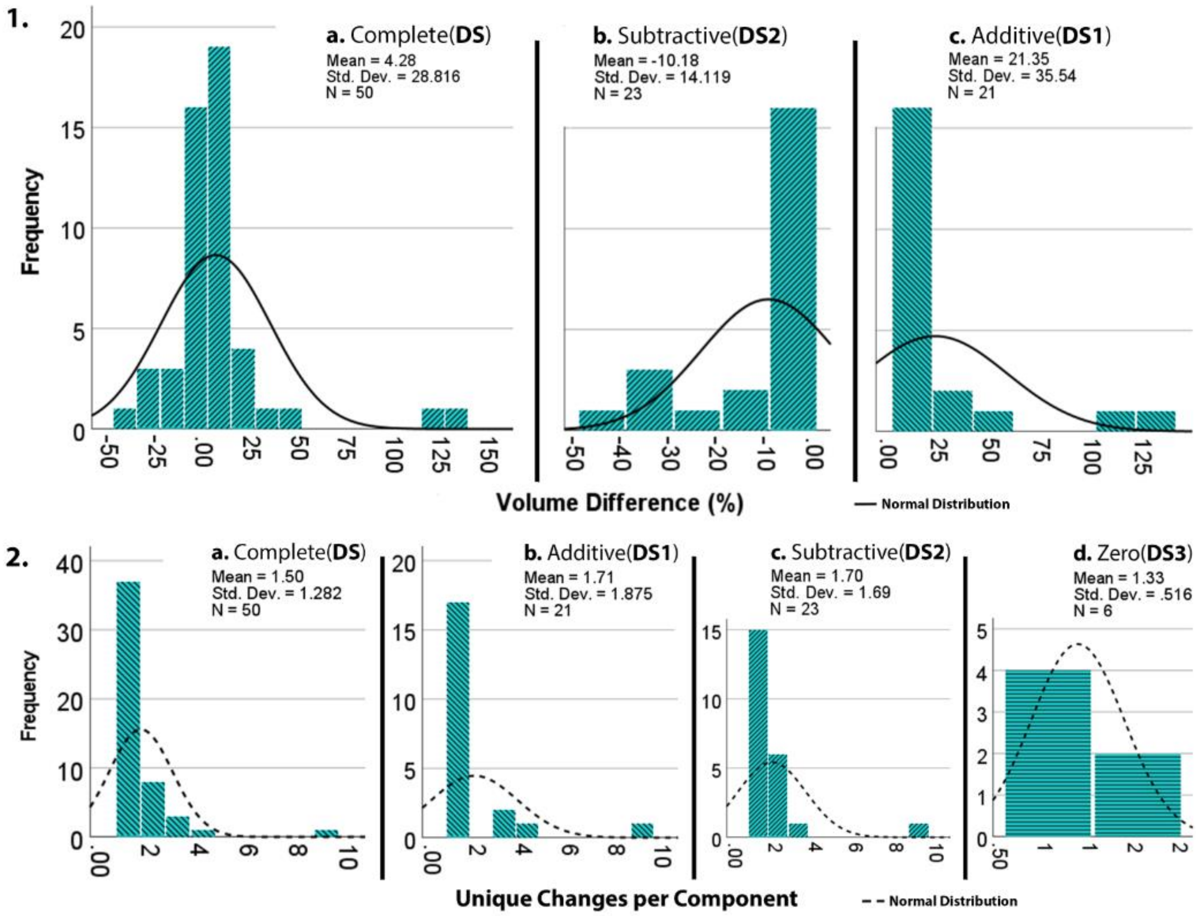

Figure 3. 1. Histograms of Volume difference (%). 2. Changes per sample (DS-DS3)

3.3 Quantitative and qualitative correlation analysis

Investigating Qualitative and Quantitative relationships by correlating the qualitative properties of a change to the physical scale of change affected permits a novel perspective into the causality of change between versions. Figure 5 provides a summary of the results using boxplots to identify mean values, data dispersion, and the skewness of correlations per dataset. Summary results for DS are firstly presented, followed by a comparative analysis of DS1 and DS2 plots to identify distinctions between additive and subtractive samples.

https://doi.org/10.1017/pds.2023.211 Published online by Cambridge University Press

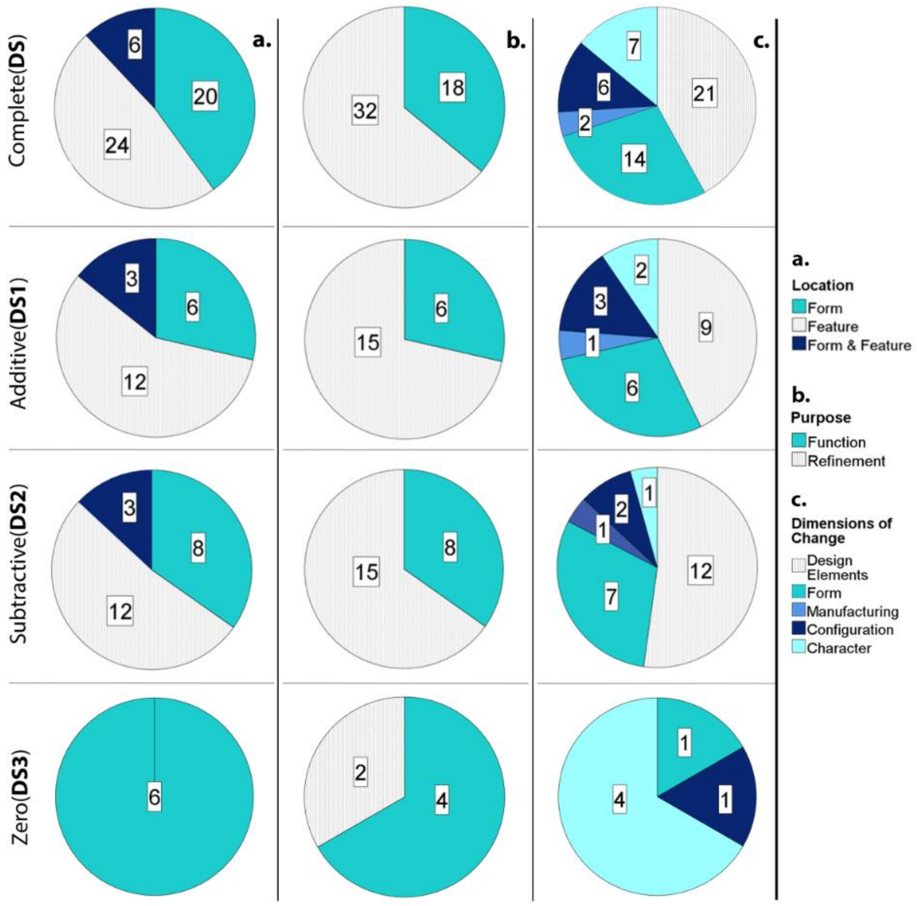

Figure 4. Qualitative frequency statistics. Datasets (DS-DS3) presented by row, with columns showing metrics for each DS: a. (Location), b. (Purpose), c. (Dimension).

For summary results (DS): Dimensions(a.): Design Elements (DE) exhibit the largest interquartile range (IQR) of the dimensions, with the greatest dispersion of volumetric difference measured between samples. Form (FM) appears normally distributed and ranging between +/-4% suggesting scale variation to fall roughly within the wider sample mean (Table 3). Manufacturing (M) has few samples (4%), of those detected the IQR appears normally distributed and changes small in scale. Configuration (Co) features the second largest IQR with a distinctly negative skew. This highlights subtractive (Co) changes to be more variable in scale, however the sample (12%) is perhaps insufficient to generalise. Character (Ch) shows a positively skewed IQR with changes often additive and small in scale (14% of samples). Location(b.): Form (Fo) displays a negative skew with the scale of subtractive volume more widely dispersed. Feature (Fe) presents a finding of significant interest, where feature based changes are the largest proportion of samples (48%) their IQR is fairly compact, indicating these changes are small, and generally of a similar scale. Naturally, changes to Form and Feature (F&F) host the largest IQR with the majority of changes being net additive, up to 40%. Purpose(c.): changes related to Function (F) are more dispersed than for Refinement (R). However, where R changes account for 64% of total samples it is again of note that little variation between measured samples is detected. These findings suggest Features (Fe) in Location and Refinement (R) in Purpose are high frequency types of change, and correlated with low volumetric difference between iterations. However, in the case of Design Elements (DE) where frequency in the sample is also high (42%) a larger dispersion of change volume is observed. This finding may evidence Location and Purpose metrics to be better predictors for the scale of a change than other qualitative metrics, such as Dimensions.

https://doi.org/10.1017/pds.2023.211 Published online by Cambridge University Press

For comparative results (DS1/DS2): with the exception of Form (Fo), additive sample changes are shown to range more widely in volume to that of subtractive samples. This suggests additive (DS1) changes to be more indeterminate and is particularly true for Function (F) where the dispersion of additive changes are significantly larger. For subtractive samples (DS2), similar results are evidenced in Form (Fo) and Configuration (Co) where the scale of negative volume is also more widely dispersed. Features (Fe) and Refinement (R) appear somewhat symmetrical in their IQR showing samples to be similar for both additive and subtractive changes.

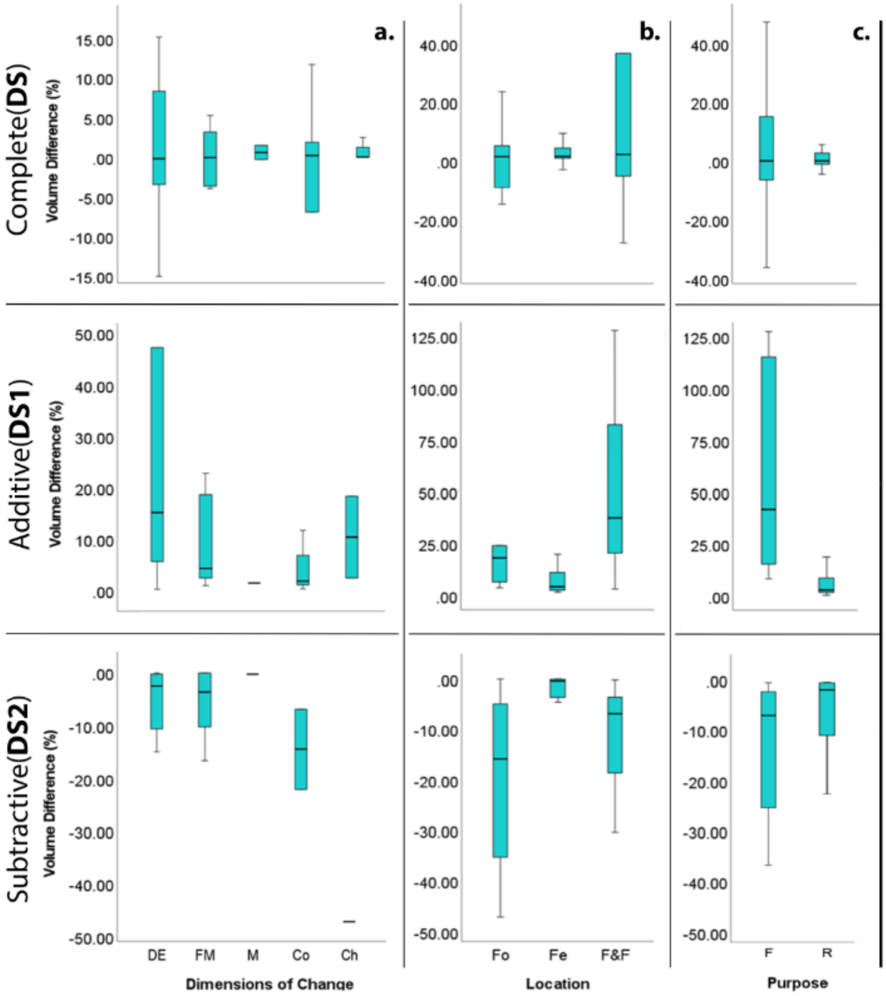

Figure 5. Comparison of qualitative metrics against volume difference (%)

DS3 Results: samples show discrete subtractive changes to be the most frequent. This is perhaps due to the nature of these samples as changes are often fine surface refinements such as texture, or tolerancing and therefore not detected in the study. Design reconfiguration, for example changing the location of a feature without changing the overall volume is also often seen in DS3 samples.

4 DISCUSSION

Where this study shows a breadth of initial results the discussion is focused on those most relevant to rapid prototyping and their impact in relation to current practice. The following points provide a summary of the key findings from this investigation, the aim of which, towards a primary characterisation of changes from a representative sample of prototype data.

- Singular changes are detected for 74% of samples.
- Changes range from -47.1% to 127.4% in volume with an average of 4.2%.
- Changes are more often subtractive than additive or hybrid at 37.3%.
- Hybrid changes are the second largest proportion of changes in the sample with 34.7%
- IQR results show additive changes are more dispersed in volume than subtractive.

https://doi.org/10.1017/pds.2023.211 Published online by Cambridge University Press

- Qualitative results show the 'average change' is a feature refinement, assuming new knowledge of design elements (DE).
- Features (Fe), and Refinement (R) are the most frequently detected qualitative changes (48%, and 64%) and both correlated with small-scale volumetric difference.
- In cases where no difference is detected, a reconfiguration of features is often observed.
- Subtractive (DS2) samples often have multiple changes 37.4% compared to 19% of additive (DS1)

By better understanding how prototypes change at both a quantitative and qualitative level, prototyping platforms, and further strategies can be better prescribed to support prototype development in NPD. Findings from this study show that the rationale for a design change, often plays a significant role in the scale of change affected. Further, this study identifies some change 'types' to be more prevalent than others, with refinement as the most frequent 'purpose' for a change, and 'feature' its location. As prototyping research aims to reduce iteration time and cost, such characterisations of change may allow for the development of more targeted prototyping strategies offering the capability to rapidly iterate between part versions. One approach is remanufacture (Real et al. 2022), where additive and subtractive processes are leveraged to directly implement version changes on an existing part. By understanding the characteristics of changes that such strategies should support, from change detection through to execution, the capability of platforms can be more aligned with the requirements of prototyping. To outline a basic set of requirements based on the findings of this study, platforms to support proto- type iteration should be natively hybrid (additive/subtractive), capable of targeting predominantly one, or more locations with or without part reorientation, and able to accurately detect and implement small- scale localised changes. Of samples analysed, the minimum volumetric difference detected was 3.6 mm^3(0.3%) for additive changes, and -1.2 mm^3(-0.1%) for subtractive. The avg. volume of change in the sample data was 4.2% or 1942 mm^3 based on the avg. V1 sample (Table 1). Whilst the points above reflect on the implications of this work in terms of physical characterisation, findings related to qualitative aspects of iteration highlight further avenues for research. Most prominently, investigating how prototype iterations change over time from a situated perspective can offer significant insight as to the ways in which designs evolve, and the practices of designers involved in their development. This study finds that a vast majority of samples feature a single change between iterations and are often for the purpose of refinement, supporting the notion that most product development involves the steady evolution of an initial design (Clarkson et al., 2004). **Study Limitations:** whilst the method affords a large number of samples to be evaluated, results could be indicative of the stage of prototype, rather than of prototyping in general. For different prototype stages, there could be different results, in particular to do with the volume, and spread of change. The method also introduces bias towards parts designed for desktop 3D printing as the majority of parts shared are designed by users with consumer 3D printing equipment. Furthermore, the experience level of designers is unknown, thus difficult to differentiate between the habits of a professional design engineer against a hobbyist. A study of this nature could provide better insight to the practices of professionals. Future works using prototype capture methods such as pro2booth (Erichsen et al., 2021) could allow for a broader range of prototypes to be evaluated across different stages. Where this study considers volumetric difference as the principal measure of change, other measures, for example performance related evaluation could provide additional insight. Finally, this study raises a number of additional questions for research, notably, to what extent are changes in the dataset influenced by the tools available to make them? and, would different tools shape the changes that designers make?

5 CONCLUSION

This study examined the characteristics of design changes in a sample dataset of 50 real-world proto- types. Samples were each analysed and evaluated against a set of quantitative and qualitative metrics to provide a range of descriptive statistics for the changes detected. Results show that the reason for a design change is, in certain cases, highly correlated to the scale of change measured between versions. Certain types of change are observed to be more common amongst samples than others, and the scale of change on average to be small between versions (4.2%). The implications of this work give direction to future research exploring prototyping strategies to implement rapid physical design change, such as remanufacture (Real et al., 2022), and their wider applications in NPD.

https://doi.org/10.1017/pds.2023.211 Published online by Cambridge University Press

ACKNOWLEDGMENTS

This research was undertaken as part of the Twinning of Digital-Physical Models During Prototyping project at the DMF lab, University of Bristol (http://www.dmf-lab.co.uk) and is funded by the EPSRC, Grant reference (EP/R032696/1). The authors would also like to thank thingiverse.com and their users for open access to model resources.

REFERENCES

Brown, T. and Katz, B. (2011), “Change by design”, Journal of Product Innovation Management, Vol. 28 No. 3, pp. 381–383.

Camburn, B., Viswanathan, V., Linsey, J., Anderson, D., Jensen, D., Crawford, R., Otto, K., et al. (2017), “Design prototyping methods: state of the art in strategies, techniques, and guidelines”, Design Science, Cambridge University Press, Vol. 3, available at:https://doi.org/10.1017/DSJ.2017.10.

Camere, S. and Bordegoni, M. (2016), “A lens on future products: An expanded notion of prototyping practice”, Proceedings of International Design Conference, DESIGN, Vol. DS 84 No. 21100509737, pp. 155–164.

Clarkson, P.J., Simons, C. and Eckert, C. (2004), “Predicting Change Propagation in Complex Design”, Journal of Mechanical Design, American Society of Mechanical Engineers Digital Collection, Vol. 126 No. 5, pp. 788–797.

Elverum, C.W., Welo, T. and Tronvoll, S. (2016), “Prototyping in New Product Development: Strategy Considerations”, Procedia CIRP, Vol. 50, Elsevier B.V., pp. 117–122.

Erichsen, J.F., Sjöman, H., Steinert, M. and Welo, T. (2021), “Protobooth: gathering and analyzing data on prototyping in early-stage engineering design projects by digitally capturing physical prototypes”, AI EDAM, Cambridge University Press, Vol. 35 No. 1, pp. 65–80.

Mathias, D., Hicks, B. and Snider, C. (2019), “Hybrid prototyping: Pure theory or a practical solution to accelerating prototyping tasks?”, Proceedings of the International Conference on Engineering Design, ICED, Vol. 2019-August, Cambridge University Press, pp. 759–768.

Real, R., Snider, C., Goudswaard, M. and Hicks, B. (2021), “Dimensions of knowledge in prototyping: a review and characterisation of prototyping methods and their contributions to design knowledge”, Proceedings of the Design Society, Cambridge University Press, Vol. 1, pp. 1303–1312.

Real, R.M., Snider, C. and Hicks, B. (2022), “Exploring the Benefits of Remanufacture during Product Prototyping: A Cost and Time Based Analysis”, Proceedings of the Design Society, Vol. 2, pp. 573–582.

Sanfilippo, E.M. and Borgo, S. (2016), “What are features? An ontology-based review of the literature”, Computer-Aided Design, Elsevier, Vol. 80, pp. 9–18.

Schon, D.A. and Wiggins, G. (1992), “Kinds of seeing and their functions in designing”, pp. 135–156.

Schrage, M. (1996), “Cultures of prototyping. Bringing design to software”, Design Management Jounal, Vol. 4, pp. 1–11.

Townsend, J.D., Montoya, M.M. and Calantone, R.J. (2011), “Form and Function: A Matter of Perspective”, Journal of Product Innovation Management, John Wiley & Sons, Ltd, Vol. 28 No. 3, pp. 374–377.

Yang, M.C. (2008), “An Examination of Prototyping and Design Outcome”, Proceedings of the ASME Design Engineering Technical Conference, American Society of Mechanical Engineers Digital Collection, Vol. 3, pp. 497–502.

https://doi.org/10.1017/pds.2023.211 Published online by Cambridge University Press