DATA AND PRODUCT DEVELOPMENT: A DATA PRACTICE PARADIGM FOR DESIGN, MATLAB SOFTWARE SENSOR DATA VISUALISATION FOR DEVELOPING DESIGN PROJECTS

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Abstract
This paper discusses how MATLAB software was integrated into the research and design process by capturing and visualising data to inform a 4th year capstone undergraduate industrial design product development project. Examined within the project framework are perspectives on; data for design projects from the literature, data collection, understanding project data, designer alternate skill set, using data to justify design direction, associated data capture technologies, data driven change of state for UIs (User Interface) and a proposal that designers have a data practice paradigm. As technology rapidly embeds into almost every aspect of society, data is produced and captured at a diversity and scale previously unparalleled. Tools and systems to capture and assess such data at the same time are being democratised, bringing new understandings, or ability to test a hypothesis more easily with sensor based open-source hardware microprocessors and commercial data capturing systems. Designers developing smart products, smart system proposals, and IOT devices need to integrate these alternate tools into traditional product development and research processes. This is especially significant in projects where subtle technical innovation and application of new technologies, “technology epiphanies”[9], or new user interfaces are present. These themes are particularly important to designers at present, engineers, data scientists and computing scientists are applying data analysis techniques to design problems previously in the product designer’s training skillset. An applied understanding of such processes permits designers to gain back control over domains slipping into the grasp of allied product development disciplines. Using a project as an example; an electronic mountain bike geometry adaptation device, a project framework is discussed around the importance of multi-signal data analysis skills for new product development in the forming of design projects involving testing of a hypothesis, control systems and natural user interfaces (NUI).

Keywords: Data, MATLAB, user interface, TUI, NUI, product development, control systems, Arduino

1 INTRODUCTION
As products become more connected and digital, and as machine learning creates new interactions to collected data, designers need an understanding on how this data is appropriately collected and utilised, and how this can augment their conceptual thinking around solutions. A discipline specific data practise paradigm for undergraduate students needs to be developed around quantitative data, currently the waters are murky for product design in relation to data practices, we can learn from our colleagues in the computing and hard sciences, however, a defined flexible model suitable to design is needed, a carbon copy is not appropriate. Qualitative research methods taught in undergraduate programmes suit many design problems and practices, however the diversity of projects and evolving practices in industry around quantitative data needs attention. Final year undergraduate product design major research projects take many forms; from highly conceptual to incremental innovation, highly technical to low technical, form driven to function driven, research driven to development driven, market ready to crude conceptual mock-up, degree programmes assessing an equal balance or varying degrees of each distinction. Nuances between product and industrial design programmes, and school to school, guide where the focus may be, all programmes however striving to get a well-balanced demonstration of prior learning in a focused project. What is needed to meet future challenges of designing products is working with quantitative data, “With data and machine intelligence being the design material of the future..”,

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Some experience using data on at least one part of a major design project is essential for young designers no matter the type of project. As an example, collecting Tall-Data or Fat-Data, rather than qualitative thick-data on an existing product performance may help young designers conceptualise how their product may better function, or be augmented with real-time machine learning, and therefore enriching design concepts beyond non-smart products.

2 THE IMPACT OF DATA ON DESIGN

The most significant recent impact on the design profession is dealing with data in at least part of the product development process somewhere between conceptualisation and end of product life, the “datafication and digital transformation of society change design professions on a profound level”[13]. The digitisation of everyday domestic products from connected smart products to IOT, through to material tracking for the circular economy, all centre on data in some way. The “success of product design hinges increasingly on the manufacturer’s capability to handle data.”[4]. Designer training needs to address the use of data in some aspect of product development. According to Pavliscak in her 2015 book, Data-informed Product Design she postulates in relation to data use, “there is not much information on how to bring it all together to design products and services” [11]. From an engineering product design perspective “Data can be accumulated through different phases of a product’s lifecycle including design, production, distribution, usage, maintenance, upgrade and recycle”[4], essentially all product development phases are open to some form of data utilisation. As discussed by Gartner, Pietzsch and Frye in 2017 “the differences between industrial design and engineering design have become increasingly blurred” [3], their training approach is quite different, however the skills and ways of thinking needed for connected adaptable products and services overlap the two disciplines [3].

2.1 Data use in design to reduce assumptions

Reducing subjective assumptions from the product design process especially at the front end of a project allows deeper reflection of functionality or feature design in the backend. As discussed above by Hou, Liang & Jiao, data can be accumulated at multiple points in the lifecycle of a product, as well as multiple points in the product development phases. Professional designers, let alone undergraduate students completing major product design projects, cannot verify with data or even literature research, all aspects of their design decisions. Ideally, data guided research should be used for at least one of the product development activities in the product development cycle.

2.2 Product feedback loop

The UX interaction community and TUI discipline use a data driven feedback loop [13]. This drives concept testing and adaptation. From these disciplines there are highly polished research project examples, however examples tend to have a crude design aesthetic and focus on interaction rather than the well-designed physical object. They spend more time on prototyping the interaction creating a feedback loop, whereas product designers focus on the object and simulate how the product will be used or interacted with. A combination of both methods, a polished visual design, and a polished interaction is ideal. You see a push to necessitate this data-driven-feedback loop within product design schools. However as discussed above, this is logistically difficult due to the scale of undergraduate product design projects. There is a tension, and competition between computing and design disciplines, computing scientist relying on data to design, and designers rely more on experienced based intuition. Designers are focus on non-smart products, lifeless non digital products that are continuously commoditised to the point of disinterest to the public and therefore a shrinking new product development area. The generally more interesting design projects blend the two methods, it could be argued, a designer with data capture and development skills using data guided intuition, not just ‘intuition’[2] would be better placed to develop projects with greater projected vision. In product design, where the problem or requirements are not necessarily apparent, or “the client's brief will be vague, it is only by the designer suggesting possible solutions that the client's requirements and criteria become clear.” [2]. Moving into the future, student product designers with experience using quantitative data somewhere in the ‘data loop’ will gain deeper insights into product development previously either inaccessible or practically too difficult to complete.
2.3 Data capture practices vary across disciplines

Design problems and projects are varied, and so too are the types of data required to considerably propose an effective solution. Where a student project starts, either at the defining of the problem phase, or after the problem has been clearly defined, influences how to approach a project, and therefore what type of data is to be accessed or collected in the investigation or validation phases. There are many factors influencing the design process research strategy, and therefore data collection methods. However, in the sciences, clear research paths have been established with a long history of scientific method defined. From the onset, students receive a clearly defined investigation, with clearly defined research processes, and therefore have a ‘hit the ground running’ approach to data capture and evaluation. Design projects are different, problem identification and problem-solving approaches are diverse. The value of a designer is not in the pre-set design project with pre-set methods and a closed brief, design thinking training is about approaching problems without a pre-set strategy, the wicked problems and the ill-defined is where designer’s skills are valued, pre-setting all aspects of a design project reduces the student training in defining a project with ‘appropriate to the project methods’, whatever they may end up being. As discussed by Pavliviscak in 2015 “There is a lot of hype about data-driven or data-informed design, but there is very little agreement about what it really means”[11]. ‘Big-data’ defines large data sets, ‘thick-data’ ethnographic interviews and surveys. Big data is further apportioned into, “Tall Data where the number of observations is large and Fat Data where the number of variables is large”[7]. Scientific engineering data approaches to problem solving tend to be “theory-based models, these encapsulate cause-effect relationships between variables that have either been empirically proven or theoretically deduced from first principles.”[6], essentially data is collected between small changes in variables within designed experiments, a ‘Black Box’ approach to deduce performance. This “engineering design process generally encompasses; the requirement analysis, conceptual design, embodiment design, and detailed design phases, which is enacted through a cascading mapping of design decisions regarding customer needs, functional requirements, product architecture, and the end-product specifications”. [14] Big data is often collected without a goal or experiment in mind, [6] and analysed to identify insights or patterns. Blended or hybrid approaches such as “Theory-Guided Data Science”[6] and ‘big-thick blending’, as Bornakke & Due discuss in their 2018 article, methodologies in how to approach blending of data sets, they suggest this requires data analysis expertise across data analysis disciplines, Bornakke & Due conclude their article stating “Blending thus joins with the growing choir of digital-based scholars who suggest that social scientists abandon the historical ideal of the renaissance person, bound to the individual but genius scholar who masters all methods” [1], this statement was made without even including engineering theory based data collection methods. This highlights the challenge of data collection for design projects, and what data collection and analysis methods should be used for design projects, or, more importantly, what methods we utilise when training and testing our undergraduate designers. This highly multifaceted methodological decision needs some form of resolution if product design degrees are to stay competitive or relevant as HCI graduates take on traditionally held product design ground. Adding; quantitative data capture, data analysis or data responsive design to at least one phase of the design process in undergraduate product design courses would help designers stay relevant. One trialled approach, to be discussed below, is the capturing of scientific engineering variable data, which, for undergraduate projects may prove appropriate. Using this method, it was possible to identify variance in the data, this guided project parameters and added a level of quantum to the project. And like many student design projects, completing all aspects of a design project, essentially producing market ready products, is unrealistic due to time, money and infrastructure. However, like the building theoretical blocks of scientific knowledge, the ‘yes I think this is feasible’ building blocks of a product design project can be fortified with data, and thus improving design project justification. At the same time preparing undergraduate students to gain rather than lose ground to allied disciplines in the competitive world of new product development.

2.4 Student project overview

This trialled student project uses a 4th year Undergraduate Industrial Design project as the lens to examine an approach to data use for new product development. The project focus considered “How can electronic integration read terrain and provide a reliable geometry adjustment system for mountain bikes” this project question was deduced after initial research and market gap identification around mountain bike geometry affecting stability and performance. The sport of mountain biking is very
popular, with a number of sub-disciplines coming under the mountain biking category, each with particular preferences for certain frame geometries. Bike dynamics and geometry are quite complex. More recently work has been done to explain stability and bicycle control, computational models have been developed to support dynamics assessment, however “The relationship between design and behaviour is shown to be heavily speed-dependent and complex” [12]. Vehicle dynamics define non subjective aspects such as stability and dynamics, how a bicycle feels to the rider is “subjective opinion”[8]. There are a number of ‘knowns’, such as changing the head angle increases or decreases stability and responsiveness at different speeds depending on the angle, a short chain stay provides a more dynamic ride in the back end of the bicycle, these aspects that are explained in the literature along with a number of other relationships. With a bicycle, even small changes in the basic variables such as changes in bicycle geometry, rider height, weight, skill, coupled with varied course routes that include slow, fast, inclines and declines, all influence the feeling of stability. Therefore, there are a multitude of variables making mountain bicycle performance difficult to evaluate. The student identified a dynamic responsive system to adjust geometry to increase bicycle handling characteristics based on speed, and incline would make sense. The system would adjust on the fly to suit stability vs power geometry depending on conditions and rider preference needs, a product design approach rather than an engineering approach is needed to produce a product concept within the timeframe of an undergraduate project.

2.5 Data collection and data processing for visualisation and real-world workflow
Keeping student projects simple enough to execute, and at the same time with enough research training, it was decided that collecting quantitative data that verified bicycle geometry stability through MOU sensors rather than opinion would be the approach. MOU sensors come in a number of forms, from high-calibrated research equipment through to inexpensive Arduino board MOU add-ons. Capturing quality data accurately required at least four considerations; repeatability, accuracy of test equipment, test rig design, data processing, and visualisation. Immediately there is a test complexity that is a yearlong project in itself. This was a design project, not an engineering project, there was no test lab, and no high-end test equipment available. Research equipment commonly comes with proprietary software to aid in data capture and visualisation, accessing this was not an option for this project. The data collection approach was formulated through how the data could be visualised using software. Python, R and MatLab are commonly used in teaching environments to visualise data, MatLab more specifically is used in engineering and data analysis[10]. MatLab, “Rather than relying on some foundational knowledge of coding or computer science policies, MatLab instead allows users to get a more intuitive read on their data”[10], this coupled with; accessible proprietary software training, integrated smartphone accelerometer and GPS data capture software, and Simulink, MatLab integrated ecosystem of products lent the selection towards MatLab. Visualising data is one thing, utilising this for machine control or machine learning is another, Simulink would support an experimental workflow for this development in a real-world application, therefore supporting the appropriateness of MatLab as a tool for this application. As discussed, design projects and design problem solving methods vary, there is not a discipline specific data practise paradigm for product design or industrial design, therefore, due to product development practice links with engineering disciplines, MatLab was trialled. It was also decided that the MatLab ecosystem could support an array of design projects from big data sets, often used to identify issues relating to ‘wicked problems’, through to engineering data analysis and machine control.

2.6 Data capture approach
What does mountain bike stability look like in data, this was the first student project question needing to be answered, question two was to confirm if this was measurable. Stability would be assessed through an absolute frame and handlebar direction field testing experiment, a higher variance indicating less stability. There are other ways of accessing stability, however these were discounted to reduce the number of variations to the experiment.

2.7 Student project outline
Developing a faultless experiment in the context of a design project in an undergraduate product design degree in all but the simplest projects would be unrealistic as discussed above. However, in setting methods and parameters for this experiment, reducing variables and increasing repeatability with
resources accessible was the goal. Quantifiable in-the-field testing results for stability are not freely or identifiably available for mountain bikes, this may be due to the mountain biking industry infancy, or a desire to keep proprietary knowledge secret. Either way, data was not available and so needed to be captured by means accessible by the student. A broad overview of the data capture experiment will be covered below for context and is not an exhaustible discussion of the experiment.

Aim - To run an experiment to quantifiably classify a difference between two mountain bike geometries. Expert sponsored team riders identify a difference between lively and slack/stable geometry mountain bike setups in the industry, however these are based on professional opinion not quantifiable data. The project aimed to collect quantifiable variance data.

Hypothesis - That it is possible to identify variance and classify variance between absolute frame and handlebar direction of two mountain bike geometries in a real-world environment by logging azimuth, pitch, roll and MALMS to identify lively and slack geometry.

Methods

Equipment - To assess stability, a rig was required, this included two smart phones running MatLab Mobile, the MathWorks data logging app, a mountain bike with a two setting manual geometry adjustment system, and stable phone mountings to secure the two smart phones.

Environment - A 140-meter section of test track was identified for the in the field data capture. This included cross country inclines, declines and corners, hypothetically some sections favouring ‘slack/stable’ geometry and other sections favouring ‘lively’ geometry.

Process – To reduce variability in time to complete the course, trail runs were carried out until there was consistency in rider performance. Then, data logging test runs were completed, the most consistent time-based logs were used for comparison between the two different mountain bike geometries for stability comparison. Using smart phones running MatLab mobile; azimuth, pitch, roll, MALMS and GPS coordinates were logged along the 140 meter track. This data was logged, then graphed using MatLab and viewed as overlapping events, the most consistent time events were used. In the graphs a variation could be identified. GPS coordinates of the event were mapped alongside the graphs helping visualise event occurrences in the graphs.

Results

A classifiable difference between the mountain bike geometries was extrapolated from the data, supporting the hypothesis that variance between absolute frame and handlebar direction as an identifier of stability. This result is consistent with professional rider opinion. Interestingly, the student test rider identified points where stability was felt, however this did not necessarily reflect in the data, another data point maybe required to completely capture the full rider experience. However, the captured data arguably is all that is needed for the machine learning system design.

2.8 In the field experiments

‘In the field’ experiments are challenging to setup and are open to a wide variety of variabilities and interpretations. This may prove too challenging in some instances for scientific professions to engage in, the degree of difficulty for replicability of data quality in experimentation may reduce their commitment to ‘in the field’ experiments. Designers are more comfortable with making mistakes or finding variance in results, this may be an advantage for the design professions in new product development industries, and conversely, less successful for incremental innovation where the scientific process of variable reduction is possible. Designers use intuition more frequently to move projects forward quickly, this may also be said to be true for intuition of the data capture and the interpretation process. Some supporting data, not definitive data, maybe all a designer needs to move a project forward. Success of new product development in consumer item categories does not necessarily rely on data, but intuition, using a variety of inputs, including some data, may improve outcomes. We have seen many heavily data driven new products fail in the marketplace, think of Google Glass as an example. One way forward may be to encompass using data, but not relying on data, a designer data intuition product development process may serve as an appropriate method in new product development.

3 WHY IS A DISCIPLINE SPECIFIC DATA PRACTISE PARADIGM IMPORTANT

Understanding the way quantifiable data is captured, how it is cleaned for use, what patterns are discoverable, all provides a useful framework with which to work. Designers can use data; as hard and fast fact, inspiration, or as a building block for intuition, data can also be used as a design medium to
augment or adapt experience through machine learning adaptations. Identifying what a version of ‘stability’ looked like was a starting point for identifying and accessing what data is needed for machine control solutions. Some data handling programmes integrate with machine control software, so it is possible to realistically develop and experiment with machine learning to solve design problems. Simulink the MatLab addon, is a primary example of this integrated system. Further to this, identifying ‘stability’ in the data inspired a discussion around; if we can identify stability through data, and we can identify which geometry is better for the different conditions based on data, we can create not only a device that changes according to the physical condition, but it is also possible to consider an interface that adapts over time using machine learning. We can then also discuss interfaces that communicate more than basic condition settings of setting 1 or 2. Discussions around what should the product look like, what is the UI for this type of product, is it a UX interface, or a TUI interface, is it a combination of both. New product development is currently grappling with these issues, especially in the health and fitness realm. Collecting data, looking at what data might infer, then thinking about how to integrate this data usefully into a product is a valuable discussion to have with undergraduate students. Therefore, we need to develop a discipline specific data practise paradigm for product design to better prepare our undergraduate students.

REFERENCES