CHASING THE WHITE RABBIT - A case study of predicting design phases of architects by training a deep neural network with sketch recognition through a digital drawing board
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Abstract

Within this paper we propose an interdisciplinary approach at the interface of computer science and architecture to predict *design phases* using a deep neural network, based on architects' hand drawings. The overall goal of the metis projects is to provide architects with appropriate *design step* suggestions using deep learning (DL) and based on semantic information of Building Information Modeling (BIM), inspired by textual autocompletion of digital keyboards on smartphones. We describe the process of our sketch protocol study and open-source software prototype developed for sketch data acquisition with a WACOM tablet and video recordings, as well as the evaluation of the sketch protocol study and the results of the recurrent neural network (RNN) with Long Short-Term Memory (LSTM) architecture, trained with the sketch data quantified through the prototype tool. The initial prediction results of the current and the consecutive *design phase* appear promising to predict with high accuracy. Our future plans include tracking the architects design process through the labyrinth of design decision making using different mental layers (e.g. *design phases*) as filters all the way to the bottom to isolate the individual mental process of a singular *design step*.

Introduction

The world population is expected to reach ten billion by 2050 with about two thirds of the population living in the urban area (United Nations 2019). In order to meet the growing demands for residential housing, architects need to be able to work faster, more sustainably and efficiently, while simultaneously increasing architectural quality. Meanwhile, Artificial intelligence (AI) has established itself in recent years as a crucial domain of computer science for industry, research, and even daily life. Likewise, Computer-Aided Architectural Design (CAAD) and digital semantic models of Building Information Modeling (BIM) became essential aspects and everyday tools of the contemporary architectural design process. However, AI cannot be seen as a leading supportive computational method in the building sector, but promises huge potential and opportunities.

The DFG funded research project metis II aims to train recurrent neural networks (RNN) to suggest further *design steps* during the early design stages in the manner of autocompletion, inspired by the mechanisms of digital keyboards on smartphones. The intelligent system generates suggestions using deep learning (DL) and case-based reasoning (CBR) methods that analyse the design process sequences found in the training set. This approach is derived from the use of reference buildings for designing architecture - as a source of inspiration, design decisions and explicit information, and a tool for evaluation and communication (Richter 2010). We attempt to assimilate to the conversational idiosyncrasies of the designer, following the idea of the 'Architecture Machine' by Negroponte (1973). Similar to an actual conversation, the intentions of the architect needs to be clarified in the interaction between the AI and the operator for progressing and suggesting. Even more so, between an architect and its supportive intelligent system, as the designers workflow can become disrupted, if questions are answered "which are not yet being addressed, ... [implying] that more is known about the solution than is really the case" (Lawson 2004, p. 53). As sketching supports the development of ideas and intentions (Lawson 2005), and is an effective tool for communication, sketch-based interaction is a promising method for an intuitive interaction with CAAD systems, naturally integrating into the design process (Leclercq and Juchmes 2002).

In this paper we present our approach for autocompletion, as well as our sketch protocol study. We describe the process for the data acquisition, analysis and pre-processing of an architectural sketch protocol study, as well as for training an RNN with our collected sketch data acquired through dividing the sketch protocol data into *relational* design sequences, such as *design phases*, *design intention* and *design steps*, to train an RNN to detect design process patterns.

Related Work

The idea of an intelligent design assistant supporting architects design decision making is derived from the 'Architecture Machine' of Negroponte (1973) and digital keyboards on smartphones. It is to support the user by predicting and offering suggestions based on architectural design knowledge we acquired through sketch protocol studies. Sketch protocol studies are a common research tool for observing architects and their design process. The protocol study types range from ‘Thinking aloud’ studies for simultaneous reporting and explaining by the participant to retrospective studies with reporting and retracing the steps and decisions afterwards. Suwa and Tversky (1997), as well as Lawson (2004), have found retrospective sketch studies to be more natural for the sketching participants because of an uninterrupted design flow and being more true to a genuine work environment. Further, Suwa and Tversky (1997) propose video recording the sketch process for supporting the participant during the consecutive reporting in order to avoid selective recall, as architects and designers “are notoriously good at post-hoc rationalization of their processes” (Lawson 2004, p. 16). However, neither protocol study type results in quantitative data so far, solely qualitative ones.

In order to obtain quantitative results, categorisation needs to be introduced to the rich sketch data. Thus, Lawson (2004) presents the possibilities of *temporal* or *relational* segments for sequencing sketch protocols. Nevertheless, he sees only the *relational* ones are a true possibility for creating reproducible results, without “the assumption that they are also ‘capable of characterising designing”’ (Lawson 2004, p. 16). Consequently, Lawson (2004, 2005) proposes the orderless *design phases* connected via ’negotiations’: *Analysis*, *Synthesis*, *Evaluation* and *Communication*, which are similar to the loosely ’interrelated’ phases by Laseau (2000): *Analysis*, *Exploration*, *Discovery*, *Verification* and *Communication*. The two authors differ as Laseau (2000) further divides the *Synthesis* into *Exploration* and *Discovery*, while both agree on *Communication* being a separate category that is continuously accompanying the different phases. Furthermore, Barelkowski (2013) introduces *Knowledge Management* as part of the internal *Communication* of the architect with their own ideas specifically for the *Analysis* into the design process, e.g. deliberate ignorance of certain aspects, criteria or constraints, for being able to progress within the design process of controlled convergence (Buxton 2007). Thus, Barelkowski (2013) divides the *Analysis* into *Knowing* and *Understanding*.

Such quantifiable sequencing can be used to train an AI with sketch protocol data using supervised DL models based on RNNs (Sutskever, Vinyals, and Le 2014), whereat LSTM (Hochreiter and Schmidhuber 1997) or Gated Recurrent Units (GRUs) (Cho et al. 2014) are possible underlying sequence processing technologies. Further, other parameters, e.g. time, coordinates and pressure during the hand drawing process, can be traced and quantified through frequency, similarity and amount.

Approach

In this paper we propose a novel sequence learning based approach for the detection and prediction of architects’ *design phases* using quantitative data acquired through sketch protocol studies. Within the following paragraphs we present our autocompletion approach, the data acquisition and analysis of the sketch protocol study data, and the pre-processing and integration of the data into an RNN model.

For our autocompletion approach we envision a closed AI pipeline of components that recurrently inform and learn: *Quantitative Analysis*, *Training the RNN* and *Sequencing the Design Process* (see Figure 1). We draw from the field of *Human-Computer-Interaction* (HCI), specifically Human-

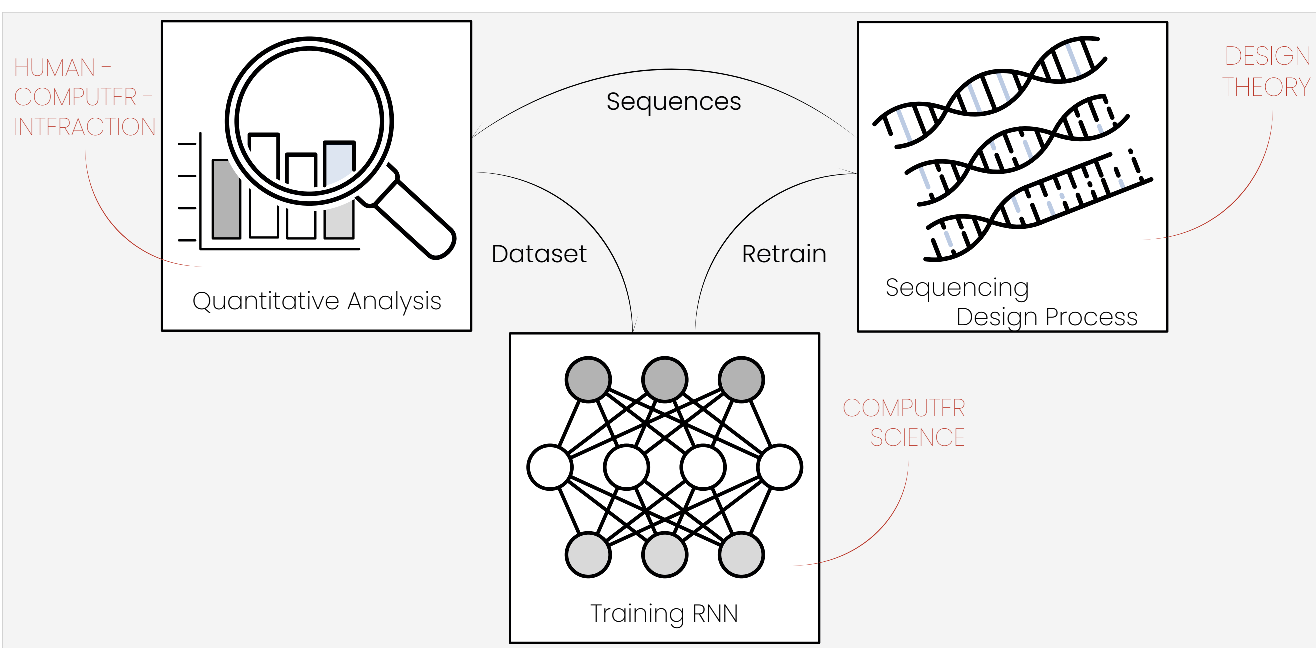

Figure 1: Envisioned autocompletion approach of the metis projects.

System-Interaction (HSI), to obtain quantifiable results of sketch protocol studies as a genuine practice of the early design stages of building design, based on sequences of the design process, found in the research field of *Design Theory*. The quantitative results of sketch protocol studies are used as a dataset to train an RNN (i.e. area of *Computer Science*), which is again used for retraining to improve the detection of sequences of the design process.

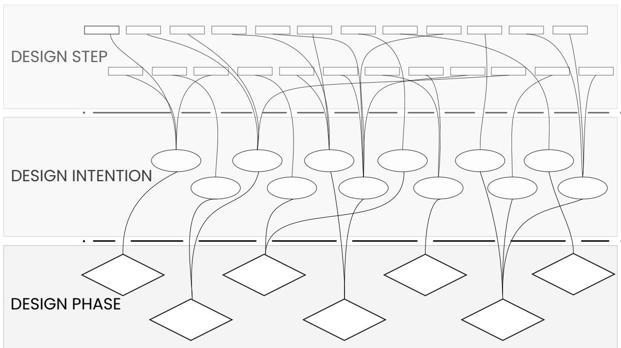

Figure 2: Visualisation of the mental layers as used for sequencing from *design step* through *design intention* to *design phase*.

We aim to track the design decision making process of architects to obtain sequences for quantifying the design process. Drawing from Lawson (2004; 2005), Laseau (2000), Barelkowski (2013), Darke (1979), and Schön and Wiggins (1992), we propose three different mental layers of relational sequences of a design decision (see Figure 2): the *design step* (e.g.'outlining parcel') as the finest clustering category, followed by the *design intention*, i.e. intention behind the executed *design step* (e.g.'requesting/requested information' by rendering the parcel dimensions tangible), culminating in the broadest sequence, *design phases*. Based on the aforementioned authors, we formulate the design process as six phases without any order, but with an overarching *Communication* to further elaborate the common *Analysis - Synthesis - Evaluation (ASE)* model: *Analysis - Knowing*, *Analysis - Understanding*, *Synthesis - Exploration*, *Synthesis - Discovery*, *Evaluation - (Informing) Knowing* and *Evaluation (- Final)* (see *Related Work* Section).

Within this paper we describe our specific approach for acquiring a first dataset for training an RNN using protocol studies, as is illustrated in Figure 3. For our study we have presented so far eight architects of different specialisation, experience level and age with the following design task:

> *A one-storey high two unit complex (52 sqm per unit), detached from the surrounding buildings, is built as a first step to extend student housing in the Olympic Village of Munich. The main facade of unit 1 faces North, while unit 2 is east-bound. One unit consists of 1 living room, 1 kitchen, 1 bathroom, and 2-3 bedrooms.*

After reading the design task accompanied by site plans and answering possible questions concerning the task, the participant draws schematic designs with a WACOM FL 0.4 pen on a piece of paper - to enable a genuine architectural design process of sketching - on top of a WACOM tablet for 15 minutes, while being video recorded. The architect can choose to place additional layers of transparent sketch paper on top or switch between any number of pieces of paper. The WACOM tablet traces the sketching, including the parameters of time, pressure and coordinates, and saves the sketch data. Afterwards the architect is being video recorded while retrospectively reporting on the design process of the sketching, while watching the previously recorded video.

After processing the video data into transcripts, one study sessions provides us with: two videos (*Sketching* and *Retrospective*), two transcripts (*Sketching* and *Retrospective*), and the *Sketch data*. To pre-process the *Sketch data* for receiving quantifiable architectural design process data, we introduce the previously described *design phases* including *Communication*, to the sketch data as sequences of the design process, as well as *architectural objects* (e.g. 'room', 'wall'). We create custom labels, which are manually assigned to the sketch protocol study data (i.e. sketch data, transcripts) (Bielski et al. 2022a), using our own open-source sketch protocol analyser tool (Ziegler 2021). The different output files in the form of JSON objects are introduced to an LSTM-based model as the consecutive RNN in our DL pipeline using the TensorFlow library (Abadi et al. 2015). The LSTM model itself includes a layer for pre-processing the quantitative aspects, namely time, pressure and coordinates, and the normalised sketch protocol data labelled with *design phases* and *architectural objects*. Based on a supervised learning scheme, the LSTM is trained with this data including temporal correlations, using a 10-fold cross validation with data samples from randomly selected time periods. The details of the mode of operation of the LSTM will be published in our paper at the ECPPM 2022 (Mete et al. 2022).

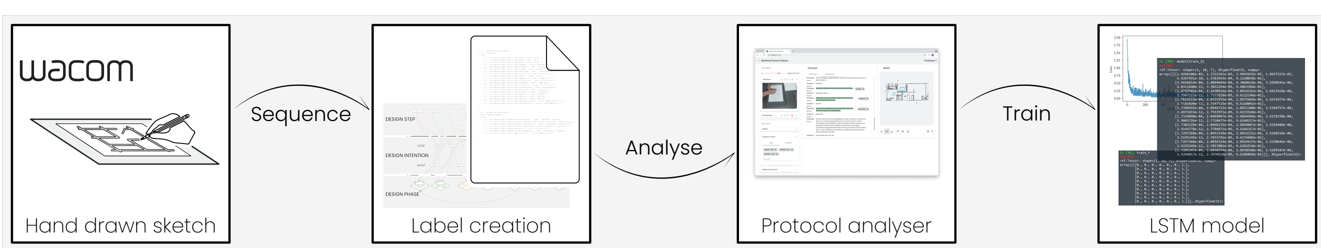

Figure 3: Process of our sketch protocol study.

Results and Discussion

The overall impact of an intelligent design assistant, suggesting further design steps, on the architect and their architectural design decision making process is to be examined for possibly hemming the creative design process and even imposing decisions.

However, our evaluation for an intelligent design assistant, suggesting further design steps enhanced with explainability, suggests that the cognitive horizon of architects is broadened by simpler and earlier access to additional information (i.e. explanation visualisations) and new perspective through other possible design solutions (i.e. design suggestions). Nevertheless, the design suggestions must be provided in a clear way as suggestions to ensure the user's ownership over the design decisions (Bielski et al. 2022b).

Further, the first results of the sketch protocol study suggest that following the design process through the mental layers of Figure 2, a domain expert can successfully assign the *design phases* to the sketch data and the transcripts for uniformly labelling the sketch protocol study data. Thus, we are able to obtain quantifiable sketch data. Furthermore, the training of our LSTM shows promising results as we are able to predict both the current and consecutive *design phase* with an accuracy of 94% (Mete et al. 2022).

The successful workflow and encouraging results need to be viewed on the background of their limitations. The researcher, an architect, labelling the sketch protocol data, has prior knowledge of *Design Theory* and analysis of the architectural design process, resulting in possible biases. Further, the amount of training data is limited (8 participants) due to a difficult recruiting process because of the COVID-19 pandemic. Finally, the *design phases* are the broadest sequencing method proposed for segmenting the architectural design process, entailing few *design phase* changes per study session: approx. 10 to 20 changes per 20,000 timestamps.

In order to remedy these shortcomings, we have taken the measures and adjustments, such as using the characteristics of the 'reflective practitioner' (Schön and Wiggins 1992) and 'primary generator' (Darke 1979) for supporting the identification of the *design phases*. To temporarily overcome the data acquisition bottleneck to properly train an LSTM, the protocol data is sliced into processing windows of fifty timestamps. Consequently, we increase the amount of data for the system to learn from and afterwards randomly separate it into training and testing data for improved data quality. Finally, in order to increase the time accuracy of the system for determining the changes of *design phases*, we define a custom loss function as an augmented version of the currently applied *binary cross entropy* loss to instead emphasise on the learning of sequence windows, which include *design phases* changes and thus, their pattern for transition.

Conclusion and Future Work

Through our sketch protocol study we explore the possibilities to track the design process through investigating the design decision making of architects using sketching on a digital drawing board for creating design autocompletion (i.e. the ultimate goal of the metis projects), as well as attempt to begin building a training set for an ANN. Our study results suggest that sketch data from sketch protocol studies can be quantified, using labels of *design phases*, derived from *Design Theory*, and our open-source sketch protocol analyser tool, based on *HCI* methods. Our *Computer Science* approach for a sequence learning based LSTM for tracking the design process by the means of these labels complements these methods to build a base training set.

So far, we have sequenced the design process of the early design stages with the broadest segmenting sequence, i.e., *design phases*. We plan to further quantitatively investigate the sketching process using the rest of the previously defined mental layers (see *Approach* Section). The next step is to consider the *design intentions* until finally, we are able to detect and predict appropriate *design steps* to suggest a continuation of the design process.

Author Contributions

Jessica Bielski (author 1) was in charge of writing the manuscript and creating the visualisations, which Burak Mete (author 2), Viktor Eisenstadt (author 3) and Christoph Langenhan (author 4) reviewed and edited. Christoph Langenhan (author 4) and Klaus-Dieter Althoff (author 6) have supervised and validated the research of the metis projects, and managed project administration in collaboration with Frank Petzold (author 5). Further, author 1 planned and conducted the study, and curated and pre-processed the collected data. Authors 1 through 4 were responsible for the conceptualisation and general methodology, whereat author 1 was responsible for the sequencing of the design process and quantitative analysis. Author 2 investigated and realised designing and training an RNN with acquired data of the sketch protocol study with author 1 and 3 as supervisors.

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