Title:
Computer Aided Creative Thinking Machines (CaXTus)

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Introduction:
This paper presents a test bed for AI technology on the integration and experimentation of creative AI (CAI) in conjunction with hybrid design tools (HDTs), environments (HDTEs) (i.e. webbased), see Fig. 1 (a) and cloud architecture, shown in Fig. 1(b) [6], [7]. The objective is to build, develop and test HDTs as assistive collaborative CAD support systems for design engineering processes (DEPs) and education.

For example, in education a paradigmatic shift in the conceptualization of learning and knowledge acquisition is observed. With the advent of multimedia technology engagement through interactivity has the potential of increasing enjoyment, and fostering new forms of creativity, social activities and learning (e.g. video teaching). The potential of artificial intelligence (AI) software that acts as a creative collaborator is envisioned. Deep Learning (DL) enables us to do things with algorithms that have never been done previously.

We take a holistic approach to address under-constrained problems, how computational aided creative thinking and inventing machines [3] can engage "wicked problems," and to benefit from AI in individual and/or collaborative creative processes (e.g. product development), shown in Fig. 2. A machine that incorporates randomness, deviation-amplification and deviation-counteracting may be both efficient and flexible. It can search for all possibilities. It can try to amplify certain ideas in various directions. It can stay at a relevant idea (which may change from time to time during the invention) and bring back to 'it' other ideas for synthesis (ibid.).

The goal is to find a set of guiding principles, metaphors and ideas that inform the development of computational support tools imbued with a CAI (i.e. CNN), new theories, experiments, and applications. Results and findings are presented of early-stage research.

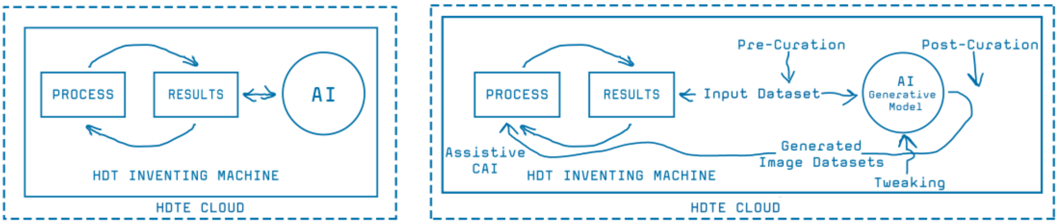

Fig. 1: Typical framework HDT and HDTE with integrated AI-CNN (a) and cloud architecture HDTs (b).

Main Idea and System HDT-CNN:
The HDTs including CAI are extended-reality (XR) that allow users physical (i.e. bi-manual) tangible interaction with real-world materials, artefacts and objects, using your foot to capture iterative steps during the process whilst simultaneously assisted by virtual and augmented realm and imbued with

AI, see Fig. 2(a). The iterative instances are captured and frozen on the screen. Computational listing and image database repository of the iterative process allows the users to access fallback choice-architecture, deicsion-making and make full use of the hybrid environment and design synthesis capabilities, shown in Fig. 2(b).

Synthesis is considered a trade-off between humans and machines in solution space optimization and finding solutions for problem-based and/or set-based problem definitions, which are framed onto multiplicity of solution exploration, choice-architecture and decision-making. The assistance and support by implementation of DL algorithms allow to take two separate neural representations of two given images, and then recombine them using a Deep Neural Network. In our study we deploy a convolutional neural network (CNN) which can be explained as an immense sequence of filters.

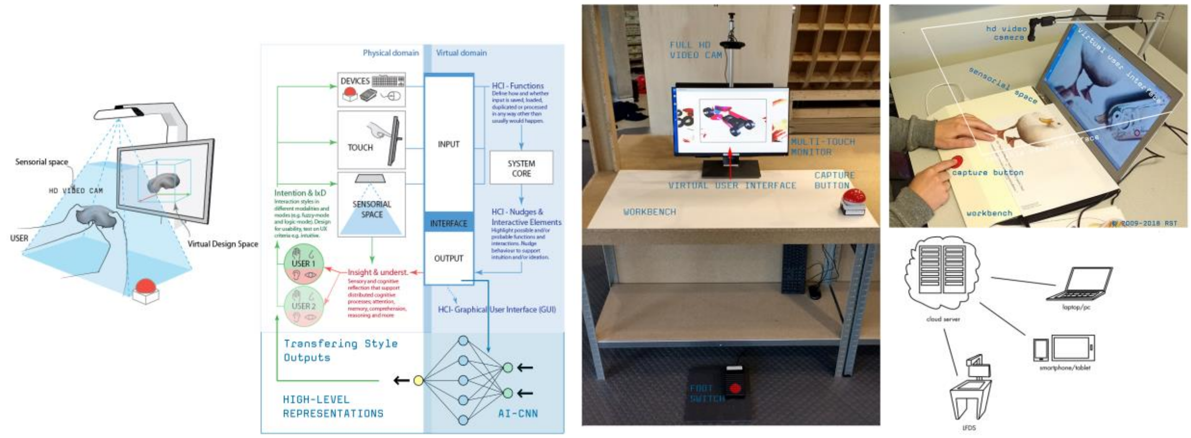

Fig. 2: Typical framework HDT and HDTE with integrated AI-CNN (a) and cloud architecture HDTs (b).

Creative, Heuristic Thinking and Blind Spots

The creative action and intention often entails the dynamic process of creativity unleashed during design and/or engineering processes (DEP). Our initial focus is on early stage (phases) of the creative thinking process (sometimes called fuzzy frontend (FFE)), wherein thoughts and fuzzy notions are transformed and represented, that often stem from the mind's eye (inner visions), metacognitive aspects, imagination, mental divisions and distractions.

Devotion and intent are fused together to bring out ideas and fuzzy assumptions to manifest 'brain generated' content through the creative force and applied as elements in the creative act. In effect it is widely recognized that designers and engineers find it hard to ignore obvious constraints, consequently ignore blind spots and/or impediments on their imagined iterative 'concepts,' before they have been fully created and/or developed [5], shown in Figure 3(a). The designer, like the consumer, is characterized by his or her experiences, beliefs, motivations, expectations, capabilities and culture. For example, the designer also has some anticipation of the eventual consumer, including some intentions for how that consumer should respond to the product [1].

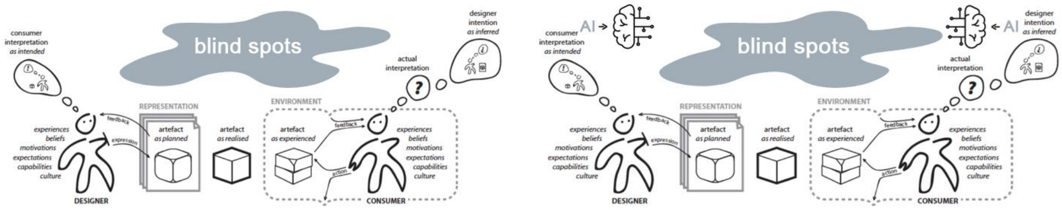

Fig. 3: The friction between intention and inference: framed as apparent blind spots (a). And framed as apparent blind spots imbued with AI (b).

Embedding AI could potentially lead to detect and identify 'blind spots' earlier and/or timely during the dynamic process of creativity unleashed during design and/or engineering processes (DEP), see Figure 3(b).

The output files of the HDTs are layered instances, see Fig. 4 and end-results are either stacked or intermediate saved instances (in fact multiple contents resources are valid as inputs) being used as original inputs for the CNN to gain a newly generated image that serves as new input during the DEP-FFE.

Fig. 4: Generic and typical results (output) HDT process (i.e. instances, merges, stacks).

Initial Experiments and Testing HDT-CNN:

After multiple iterations and additional modifications were applied to the shape of the network, such as exploring the effects of a convolutional shape, which implies descending the number of neurons as the layers progress. The results became more promising, and once applied to a general image (stack) created by an HDT, as shown in Fig. 5, the results, see Fig. 5(b) and Fig. 5(c) were already starting to look a lot more like the original input, Fig 5(a).

(a) (b) (c)

Fig. 5: Left original image (stack) (a), middle image-representation CNN (b), right excerpts generative process (low-resolution and low-level features) (c).

Style Representation and Transferring Style

The essential trick that makes it possible in a Neural Network (NN) to learn how to recombine high-level representations all the way up from the identified lower-level features in its other layers, is through the optimization function (i.e. cost function). This function allows the network to compare its output (i.e. predictive) with the actual goal (i.e. target). The optimization function compares how close the prediction of a network is to the target, and then predicts what small tweaks need to be made to the network to improve the prediction next time. The process of prediction, comparing and finally followed by tweaking is performed countless times until the network gives a prediction (an image-representation) that is identical to the target (the original image).

This process is also called gradient descent: it is the key that allows NN to learn from their mistakes, literally. When two images need to blend by transferring style to one another, such a simple function cannot be used anymore. Instead, another solution is provided in which two 'original' images, one for content representing the object, and one image to absorb the style, are considered as near perfect (raw) representation of the original, i.e. 'content representation' [2]. In such, the NN recreates the original style image as a 'set of lower-level style representations.' Instead of averaging the pictures, as a result, it adapts the higher-level features of the content image to be recast using the lower-level features of a given style representation. Therefore, the style will look and feel the same as the style-representation, while the objects displayed in the content-representation will still be recognizable as the higher-level features remain. Moreover, the function attempts to reach an optimum at which the lowest minimum possible will be achieved. Adaptations were implemented to the algorithm and these changes aimed to give the end-user more control over the algorithm's 'effectiveness' and to provide the result without having significant delays.

By allowing the network to give output as its trains, the user can already start to see what the network will be aiming for given more time. The training process makes the style representation more useful over time as the creation-process is happening. It also provides the user with the opportunity to stop the training, should the style representation become too dominant to his or her liking. An additional modification to be implemented is the addition of controllable parameters, which modify the style transferring-process, which the user can tweak and experiment with. These parameters serve as knobs to fine-tune the perceived depth of the style transfer, the (dis) favouring of style over content and the ability to boost the rate of learning of the algorithm for faster ('rawer') results.

Fig. 6: Style extraction, left original image (a) and right insertion adoptive image (b).

(a) (b) (c)

(d) (e) (f)

Fig. 7: Image transformation through style-extraction in progressions, top left original image, (a) to (f) bottom right (iterative step-samples only).

The HDTs are connected to the internet and work in a browser (i.e. Chrome), it can access pre-trained models and therefore leverage their capabilities without the need of training their own network or spending significant time on training their machine-learning-models (MLM). Several test and iterations were made, before we could apply the gained knowledge and insights to the HDTs architecture and system. Additional modifications were applied to the shape of the network, such as exploring the effects of a convolutional shape, which implies descending the number of neurons as the layers progress. The results were more promising, and once applied to a general image created by an HDT (i.e. instances, merges, stacks) as shown in Fig. 4 and Fig. 5, the results were already starting to look a lot more similar to the original and adoptive input, as presented in Fig. 6(a) and Fig. 6(b).

The implemented solution makes use of an algorithm that can extract the style of one image and inserting it into another while maintaining the contents of the original image, as presented in Fig. 7 (a–f).

Conclusions:

For problem solving and synthesis, the use of an information-processing system (i.e. thinking-machines, design-machines, teaching-machines) that creates problem representations and possible solve-for-solution searches selectively through rhizomes of intermediate situations, seeking the goal (target) situation and using heuristics to guide its search could be a promising path.

At present, we work on two suggestions (options) how these algorithms could be implemented and integrated directly in the software of the HDTs and HDTEs. The first option would be to make the algorithm apply a layer-wise-adoption. The other option would be to give the algorithm the capabilities to detect textures or different surfaces in an image. Then, the algorithm could apply specific modifications to each identified texture/surface.

The current status of the HDT-CAI system is the flexibility, the desired speed of the CNN is still a challenge. It must have undergone extensive training before being use functionally fluid and assistive in (near) real-time. Using a decent GPU (in our case NVIDIA GeForce GTX970), it takes the original algorithm roughly a few hours of training time before it’s usable.

Further research and experimentation are underway to explore and investigate other possibilities of CNN in HDTs and HDTEs. Creativity imbued with CAI is an ability to discover new ideas, define problems, discover blind spots and address challenges to solve for solutions. The paths open to curiosity are many or even too many, they are never straight or predictable, and it takes different and unpredictable amounts of time to traverse them [4].

References:

[1] Crilly, N.; Maier, A.; Clarkson, P. J.: Representing artefacts as media: Modelling the relationship between designer intent and consumer experience, International Journal of Design, 2(3), 2008, 15-27.

[2] Gatys, L.; Ecker, A.; Bethge, M.: A Neural Algorithm of Artistic Style. Journal of Vision, 16(12), 2016, 326. doi:10.1167/16.12.326

[3] Maruyama, M.: The second cybernetics: Deviation-amplifying mutual casual processes, Amer. Sci., 51, 1963, 164-179.

[4] Nowotny, H.: Insatiable Curiosity, 2016, doi:10.7551/mitpress/7814.001.0001

[5] Wendrich, R.: (2016). Hybrid design tools for conceptual design and design engineering processes: bridging the design gap: towards an intuitive design tool, Thesis, 2016. doi:10.3990/1.9789036542272

[6] Wendrich, R. E.: Raw Shaping Form Finding: Tacit Tangible CAD. Computer-Aided Design and Applications, 7(4), 2010, 505–531. doi:10.3722/cadaps.2010.505-531

[7] Wendrich, R. E.: Blended Spaces for Integrated Creativity and Play in Design and Engineering Processes, Journal of Computing and Information Science in Engineering, 16(3), 2016. doi:10.1115/1.4033217