THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

The Magic of Vision: Understanding What Happens in the Process

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Department of Computer Science and Engineering (CSE)

Division of Interaction Design

CHALMERS UNIVERSITY OF TECHNOLOGY

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Abstract

How important is the human vision? Simply speaking, it is central for domain related users to understand a design, a framework, a process, or an application in terms of human-centered cognition. This thesis focuses on facilitating visual comprehension for users working with specific industrial processes characterized by tomography. The thesis illustrates work that was done during the past two years within three application areas: real-time condition monitoring, tomographic image segmentation, and affective colormap design, featuring four research papers of which three published and one under review.

The first paper provides effective deep learning algorithms accompanied by comparative studies to support real-time condition monitoring for a specialized microwave drying process for porous foams being taken place in a confined chamber. The tools provided give its users a capability to gain visually-based insights and understanding for specific processes. We verify that our state-of-the-art deep learning techniques based on infrared (IR) images significantly benefit condition monitoring, providing an increase in fault finding accuracy over conventional methods. Nevertheless, we note that transfer learning and deep residual network techniques do not yield increased performance over normal convolutional neural networks in our case.

After a drying process, there will be some outputted images which are reconstructed by sensor data, such as microwave tomography (MWT) sensor. Hence, how to make users visually judge the success of the process by referring to the outputted MWT images becomes the core task. The second paper proposes an automatic segmentation algorithm named MWTS-KM to visualize the desired low moisture areas of the foam used in the whole process on the MWT images, effectively enhance users'understanding of tomographic image data. We also prove its performance is superior to two other preeminent methods through a comparative study.

To better boost human comprehension among the reconstructed MWT image, a colormap deisgn research based on the same segmentation task as in the second paper is fully elaborated in the third and the fourth papers. A quantitative evaluation implemented in the third paper shows that different colormaps can influence the task accuracy in MWT related analytics, and that schemes autumn, virids, and parula can provide the best performance. As the full extension of the third paper, the fourth paper introduces a systematic crowdsourced study, verifying our prior hypothesis that the colormaps triggering affect in the positive-exciting quadrant in the valence-arousal model are able to facilitate more precise visual comprehension in the context of MWT than the other three quadrants. Interestingly, we also discover the counter-finding that colormaps resulting in affect in the negative-calm quadrant are undesirable. A synthetic colormap design guideline is brought up to benefit domain related users.

In the end, we re-emphasize the importance of making humans beneficial in every context. Also, we start walking down the future path of focusing on human-centered machine learning(HCML), which is an emerging subfield of computer science which combines theexpertise of data-driven ML with the domain knowledge of HCI. This novel interdisciplinary research field is being explored to support developing the real-time industrial decision-support system.

Keywords: Industrial tomography, visual comprehension, affective colormap, automatic segmentation

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List of publications

[I] Y. Zhang and M. Fjeld, "Condition Monitoring for Confined Industrial Process Based on Infrared Images by Using Deep Neural Network and Variants", in Proceedings of the 2020 2nd International Conference on Image, Video and Signal Processing (2020), pp. 99–106.

[II] Y. Zhang, Y. Ma, O. Adel, R. Yadav, M. Fjeld, and M. Fratarcangeli, "Automated Microwave Tomography (MWT) Image Segmentation: State-of-the-Art Implementation and Evaluation", 126–136 (2020).

[III] Y. Zhang, M. Fjeld, A. Said, and M. Fratarcangeli, "Task-based Colormap Design Supporting Visual Comprehension in Process Tomography", in EuroVis 2020 - Short Papers, edited by A. Kerren, C. Garth, and G. E. Marai (2020).

[IV] Y. Zhang, M. Fjeld, A. Said, M. Fratarcangeli, and S. Zhao, "Affective Colormap Design for Accurate Visual Comprehension in Industrial Tomography", Computer Graphics Forum (under review).

[V] Y. Zhang, Y. Ma, A. Omrani, R. Yadav, M. Fjeld, and M. Fratarcangeli, "Automatic Image Segmentation for Microwave Tomography (MWT) From Implementation to Comparative Evaluation", in Proceedings of the 12th International Symposium on Visual Information Communication and Interaction (2019), pp. 1–2.

[VI] Y. Zhang, A. Nowak, G. Rao, A. Romanowski, and M. Fjeld, "Investigating How Experienced Industrial Tomography Experts EffectivelyWork with Augmented Reality", in Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems (under review).

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Contents

1 Introduction

The work presented in this thesis focuses on facilitating visual understanding for users working with specific industrial processes. Such understanding is critical for domain-related decision-making relying on the human visual systems. This thesis illustrates the research done regarding the facilitation of visual comprehension for a specific domain–industrial tomography, with respect to three realms–condition monitoring, image segmentation, and affective computing. The main skeleton of this thesis is summarized as follows. First, it provides an exhaustive background and motivation of the three realms. Then, the thesis points out the corresponding problem solving and lights up future work which will concentrate on interdisciplinary research by merging human-centered design, machine learning, and visual analytics.

1.1 Background

The research described in this thesis aims to benefit humans pertaining to get insights and in-depth understanding for industrial tomography processes. In human computer interaction (HCI), the goal for a formed framework or application is to improve their usability or accessibility to the benefit of its users.

1.1.1 Condition monitoring

Condition monitoring has been developed as a mature technique in industrial settings due to its superiority of spotting anomalies and improving productivity. For an on-going process, it is crucial to detect undesired and defective products and improve efficiency by reducing faults with production equipment. The detection and diagnosis of defects and faults via improved monitoring is an active field of research in industrial systems due to its potential for reducing maintenance costs [1]. Condition monitoring enables the comparison between regular and erroneous scenarios by use of external or built-in devices. The progressively increasing sophistication of industrial equipment brings a greater likelihood of faults due to their complexity. Therefore, appropriate and effective condition monitoring must become mandatory in the context of data-driven industrial processes.

In this thesis, we introduce a specific confined process called microwave drying for porous foams, which is operated in a confined chamber independent from the rest of the process. As illustrated in Figure 1.1, a *black-box* is used to cover the

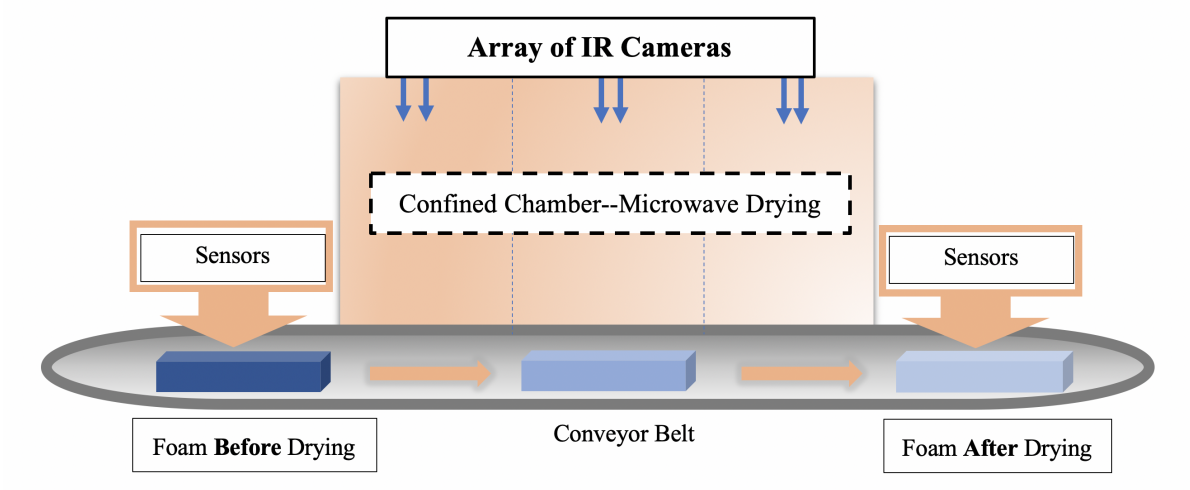

Figure 1.1: *Schematic overview of confined microwave drying of porous foams. Array of Infrared (IR) cameras are mounted on the ceiling inside of the confined chamber*

foam drying process. An array of infrared (IR) cameras is installed on the ceiling of the chamber to capture the complete process. Other sensors (e.g. Microwave Tomography Sensor, Electrical Capacitance Sensor) are employed either before or after the drying process to measure the parameters of the foam, but only the IR cameras can observe the process taking place inside the box. Thus, how to develop highly intelligent condition monitoring methodologies by making using of the IR images become the main research problem.

1.1.2 Image segmentation

A significant point to understand a process is to be familiarized with the related dateset, especially the input and output of the specialized processes. The data used to characterize the tomography included in this thesis is mainly in the form of images. Image segmentation is one of the most commonly used methods to classify the pixels of an image correctly in decision oriented applications. Due to its capability for distinguishing various features [2], it is able to divide an image into a number of discrete regions such that the pixels have high similarity within and high contrast between regions [3]. in a word, image segmentation has the high capacity to help human better visually understand the specifications by highlighting the critical information.

Microwave Tomography (MWT) is a non-ionizing imaging technique that provides a quantitative image of the dielectric profile of the object of interest (OI) [4, 5], which is used to characterize our microwave drying for porous foams process. An important physical parameter–moisture level of the foam–is measured throughout the whole drying process. Depending on the imaging techniques used, a reconstructed tomographic images can display either the location of the moisture

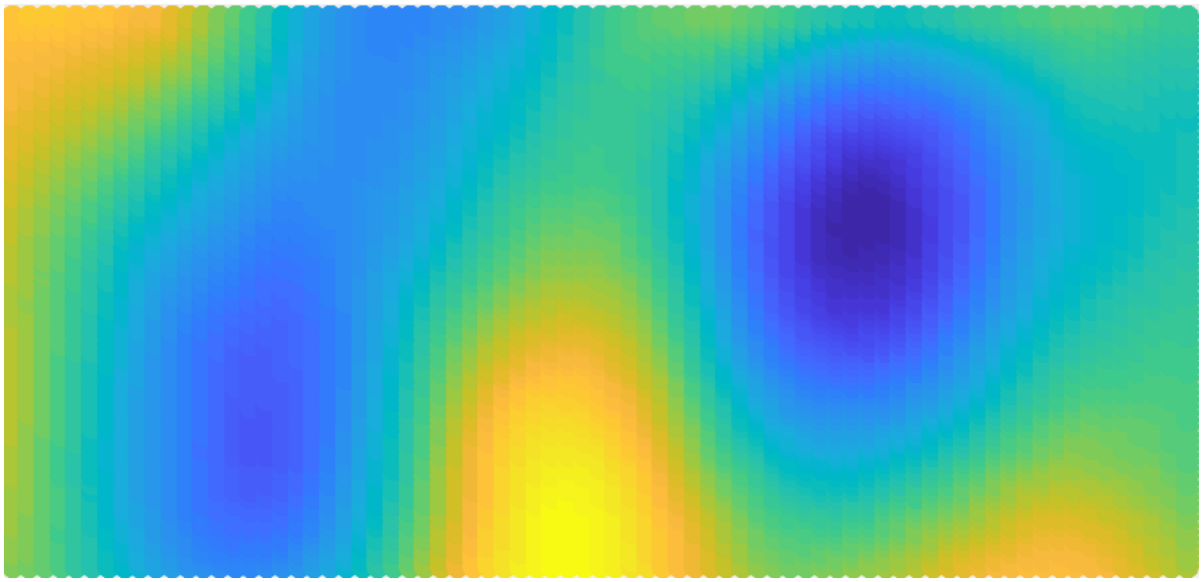

Figure 1.2: *Example of an MWT image (input image) in our study. Blue means lower moisture, yellow means higher moisture.*

through the foam as an OI or a map of the dielectric properties of the moisture value both commonly referred to as MWT techniques [6, 7]. After the drying procedure, the moisture level is represented on the outputted images, depicted in Figure 1.2, which is an example of reconstructed images using the MWT system. Different colors resemble different moisture values.

1.1.3 Affective computing

In HCI, an important starting point is deploying human-centered design to aid users to improve usability of the targeting objects. We have described that users are able to understand the critical information revealed on images by using image segmentation. However, will the precision of the visual understandability vary with the changing of related affective stimuli such as different colors? Appropriate color scheme usage in graphs, images, and animations can raise expressiveness and persuasiveness in visual representations. The goal of color-mapping is to effectively communicate these features from visual imagery to those data that are the most prominent in hands-on tasks [8]. Color is a retinal variable which is conventionally determined by hue, saturation, and brightness (HSB), all three being dimensions in perception-based applications [9]. Research has proven that using different colormaps can result in differing interpretations, depending on how the visualization is perceived by the human eye [10]. That is, the selection of colormaps can significantly influence a user's visual comprehension of data.

People react emotionally to different colormaps as well as to the visual imagery displayed by those specific colormaps. Emotions can influence how the information

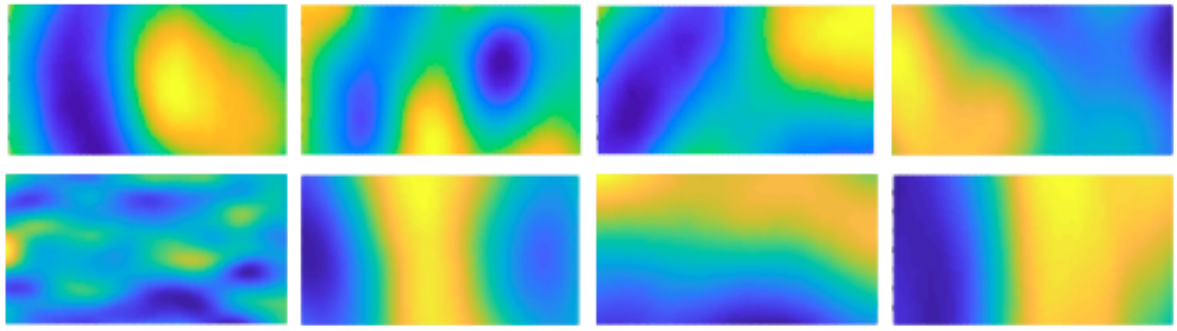

Figure 1.3: *The eight MWT image samples in our study. Different colors represent different foam moisture levels. Blue is the desired color, representing lower moisture levels.*

presented to people will be interpreted, and how people will be affected in the visual environment [11]. In our context, the outputted MWT images, offering information that can be visualized using colormaps, are central in controlling the heating process. An operator's visual comprehension of an MWT image is key in recognizing the moisture levels on images. Figure 1.3 shows the set of eight MWT image samples used in our study. Each sample was acquired from a confined microwave foam drying and reveals post-process moisture levels.

1.2 Motivation

This section presents the key motivations driving this thesis.

1.2.1 Feature engineering & feature learning

Conventional 'intelligent'methods of condition monitoring are taxonomically defined as feature engineering (Figure 1.4) [12] – also called shallow learning models [13–16]. The well-established and verified methods have already achieved considerable success in intelligent fault detection [17], but are not capable of tackling complicated faults with low amounts of prior knowledge [13]. These traditional models also have difficulties when processing complex errors, causing undesirable consequences, which motivates us to explore more functional and powerful methods for feature extraction and function computation, even in multiplex settings.

To achieve this, we propose to use feature learning (Figure 1.5) [12, 18, 19] instead of feature engineering. Feature learning makes use of algorithms that create and learn features derived from raw data, with iterative steps to continue learning from newly obtained data [12]. Deep learning [20] is typically representative of feature learning: It is a class of machine learning algorithms that use multiple layers of nonlinear processing units for feature extraction and transformation [21].

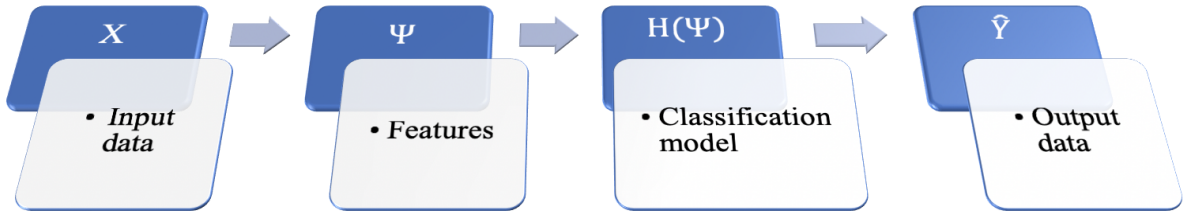

Figure 1.4: *Schematic representation of feature engineering.*

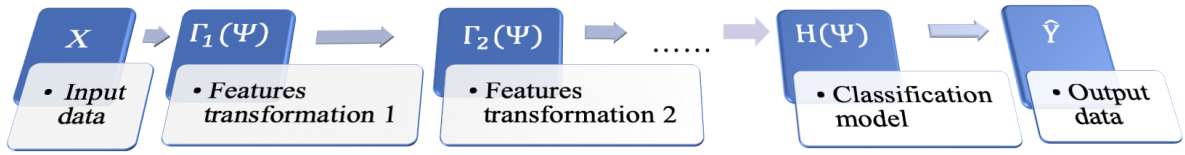

Figure 1.5: *Schematic representation of feature engineering with multiple feature transformations.*

Deep learning makes it to extract complicated features and resolve multiple complex functions, overcoming some of the shortcomings of existing methods. There are many categories of representations in deep learning, such as Deep Neural Network (DNN) [22], Convolutional Neural Network (CNN) [23], Recurrent Neural Network (RNN) [24], and others. In this thesis, the advanced feature learning is used to address the condition monitoring for microwave drying process.

1.2.2 Visualization by automatic segmentation

After drying, some regions of the foam may not be completely dry. It is obvious that dry parts have less moisture, hence the amplitude (moisture or dielectric level) of these areas is lower than in the non-dry regions. The difference between dry and non-dry is represented by allocating different colors to each region (Figure 1.2) where the blue parts stand for good/low moisture and the yellow parts stand for bad/high moisture. Dark blue parts are drier than yellow areas. The colours become more yellow when there is more moisture. It is critical for operators and practitioner to precisely assess the low moisture areas of the material so as to gauge the success of a drying process.

There are some efficient MWT systems that produce high-quality images for industrial processes [5, 7]. In our drying process, the measurement of the foams is also performed by MWT, whose detailed design is beyond the scope of this paper. We address the segmentation for visualizing the blue regions representing low moisture. Thus, we propose an automatic segmentation method called MWT Segmentation based on K-means (MWTS-KM) for processing the images

reconstructed by an MWT in our experiment. This algorithm is fully automatic and the user only has a verification role [2]. Next, we report on how we carried out experiments in practical settings to validate the proposed segmentation method, including how we successfully validated its robustness, performance and reliability.

1.2.3 Human affect and Design

Generally, a successful deployment of colormaps can not only improve the objective performance of tasks but can also arouse affective resonance, as well as raising visual immersion. To measure the effect of different colormaps explored within our study, we firstly propose a research question. RQ1: How can various colormaps affect task accuracy in the context of MWT so as to support accurate visual comprehension?

Besides, we note that research has shown how colors can be linked to affective expressions. A commonly-used approach is to encode affect with the circumplex valence-arousal emotional model [25–29] for further analysis. Emotions are characterized and plotted as a 2D circumplex coordinate system graph (Figure 1.6) with the first dimension being positive and negative (valence), and the second dimension being physically exciting and calm (arousal) [26]. These psychological dimensions of affect are significantly influenced by informative properties of colormaps, such as lightness and chroma. Some design rules for colormaps have been developed for practical uses, suggesting that the chromatic properties of colormaps are emphasized and increased in positive and exciting status and are weakened and reduced in negative and calm status [28]. This leads to the second research question. RQ2: Are colormaps triggering affect in the positive-exciting quadrant of the valence-arousal grid able to facilitate more accurate visual comprehension in terms of human perception towards MWT than those from the other three quadrants? According to Bartram et al. [27], more strongly saturated colors can be used to characterize the affect positive quadrant, while positive emphasizes higher chroma colors. Since the segmentation task, which is highly dependent on deeper colors is engaged in our study, we hypothesize that the positive-exciting quadrant is more desirable than other quadrants.

1.3 Contributions

In this thesis, we emphasize the importance of letting human understand the details of the specialized industrial processes. By real-time condition monitoring, users to able to find the process anomalies through the IR images. By MWT image segmentation, users are visually enhanced to obtain the in-depth comprehension of the output. Furthermore, the affective computing provides multiple colormaps

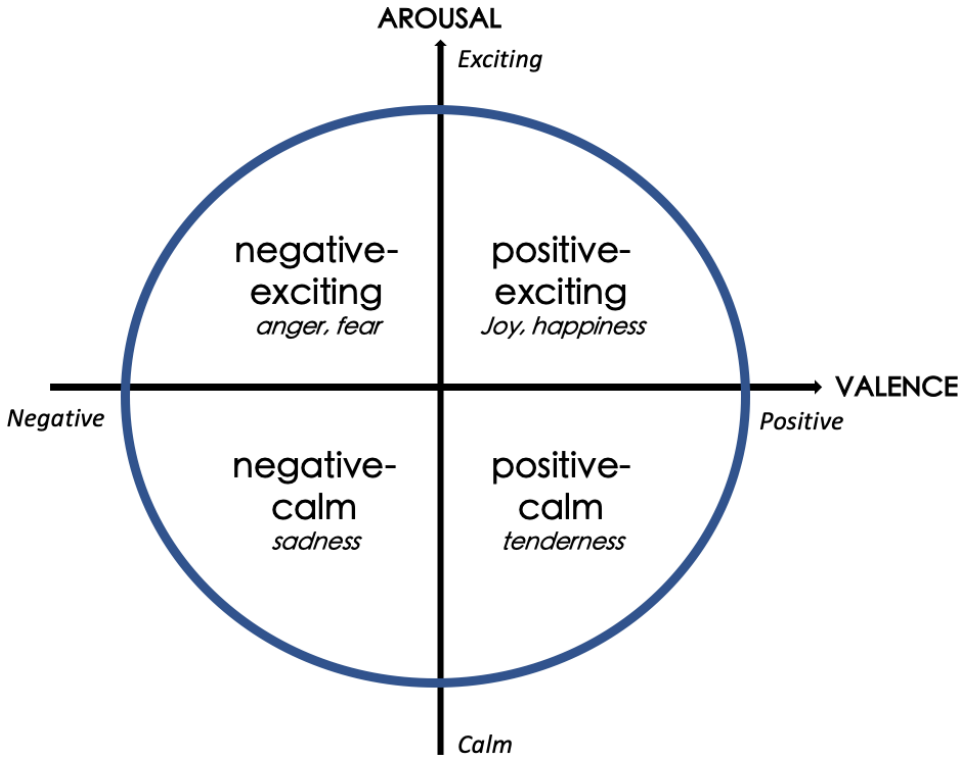

Figure 1.6: *The circumplex valence-arousal affective model used in our study. We hypothesize that the positive-exciting quadrant is more desirable than other quadrants.*

for users to connect human affect with accurate visual comprehension, so as to get more insights into the tomography-controlled processes.

1.3.1 Deep learning through IR images

Nowadays, IR imaging is widely used in industrial processes because of its excellent performance in measuring temperature differences, important when monitoring safety-critical equipment [12]. In a confined industrial process where temperature is a crucial parameter for evaluating overall performance, IR cameras and IR imaging are especially useful for monitoring process health. As illustrated in Figure 1.1, an array of IR cameras is installed on the ceiling of the chamber to capture the complete process. The main research question here is whether, through analysing the IR images, a state-of-the-art model-driven deep learning technique can in this context more effectively determine process conditions when compared to conventional methods. The contributions of our work are:

- Deriving a method to get access to monitor the confined industrial process.
- Deploying state-of-the-art deep learning with its derived methods and verifying their efficacy.

- Making use of IR images to broaden the industrial condition monitoring horizon.
- Comparing feature learning and conventional feature engineering.

1.3.2 MWTS-KM

To benefit from the output from the microwave drying process, we propose to visualize the moisture area, more precisely the low moisture area for porous foams using image segmentation methods on MWT images, on the premise that many segmentation methods have demonstrated satisfactory utilization in tomographic systems but not desirable success in the context of MWT. Regarding the contributions, firstly, a state-of-the-art MWTS-KM segmentation method is proposed to visualize the low moisture area of an image. Then, as a novel integrated algorithm, it is compared with two alternative segmentation algorithms that have been used widely in related application areas.

1.3.3 Affective colormap design

After the segmentation, users are capable to distinguish the low moisture area on MWT images by their own understanding merely. Thus, we start to concentrate on colormap design for visual comprehension of MWT images based on the same segmentation task. To balance energy effectiveness, material flow, and safety aspects, it is crucial that humans accurately interpret such images. To resolve RQ1 (1.2.3), we implemented a systematic quantitative study focusing on an MWT image segmentation task to evaluate the colormaps. To tackle RQ2 (1.2.3) and validate our hypothesis, we formulated and conducted a crowdsourced study on the same task. The following contributions are made:

- Investigating how different colormaps affect task accuracy in the context of MWT by a quantitative evaluation and obtaining the colormaps yielding the best accuracy.
- Combining conventional design study with crowdsourced study and validating that colormaps triggering affect in the positive-exciting quadrant in the valence-arousal model are able to facilitate more precise visual comprehension in MWT.
- Proposing a synthetic design guideline for relevant researchers and practitioners to select colormaps boosting accurate visual comprehension in the context of MWT.

2 Related work

A body of research has been done regarding this three specialized application fields. Deep learning for condition monitoring or fault diagnosis is ubiquitously employed in industry. Fenton et al. [30] established a research overview on fault detection in electronic systems wherein the importance of DNN was emphasized. In addition, a retrospective review of deep learning in machine health monitoring was conducted by Zhao et al. [31]. They concluded that general deep learning methods in this context are mainly from Autoencoder and its variants, Restricted Boltzmann Machines and its variants including Deep Belief Network (DBN), Deep Boltzmann Machines (DBM), CNN and RNN. Janssens et al. [12] conducted a comprehensive evaluation of feature engineering and feature learning among several industrial cases, verifying its superiority for automatically determining the condition of machine health, using IR videos. Keerthi et al. [21] also fed IR videos as input into CNN to automatically extract the relevant region of an interest's features, and subsequently make a prediction regarding their machine's bearing oil status. Their evaluation showed that the proposed system achieved an accuracy of 96.67%. Ma et al. [32] implemented a deep Autoencoder for diagnosing faults based on images and structured data. A novel model which completely extracted features by DNN and conducted analysis via a hidden Markov model (HMM) was proposed by Qiu et al. [33] to handle indistinguishable faults. For an industrial rolling element bearing (REB) fault classification process, Amar et al [34] gave an example of creating then training vibration spectrum images in DNN. Likewise, for a similar REB fault detection task, Verma et al. [35] developed an autoencoder using intelligent unsupervised learning towards vibration measurements.

Besides, significant research efforts have been invested into the topic of tomographic image segmentation and related areas of application. Sharma et al. [36] provided a review of a set of automated segmentation methods ranked by applicability and suitability in the context of tomographic images; especially CT images. Shoaib et al. [37] used the Otsu algorithm [38] to propose a method including thresholding to prove a successful segmentation in lungs using CT. Likewise, Dorgham [2] deployed an automatic segmentation method on the basis of GrabCut [39] to detect human body Regions of Interest (RoI) from CT images. Moreover, Jose et al. [40] effectively detected and identified the exact location of a brain tumor through K-means clustering and fuzzy c-means algorithms by segmentation CT images. Sheppard et al. [41] utilized a combination algorithm containing active contours [42] and watershed transformation [43] to implement segmenta-

tion for porous materials in industrial tomographic images, resulting in superb quality results. Concerning practical MWT, Wang et al. [44] employed a comparative study on MWT image segmentation for breast cancer detection. They used a K-Nearest Neighbor (KNN) algorithm and Gaussian Mixture Model (GMM) in their research, and showed that KNN outperformed GMM when segmenting Region of Interest (RoI) when using the Mathew Correlation Coefficient (MCC). Another concrete comparative study was presented by Mahmood et al. [45], who demonstrated that MWT image segmentation is even capable of ameliorating the accuracy of image reconstruction using several automated segmentation methods. Joseph et al. [46] integrated image segmentation with their inverse scattering algorithm called Forward- Backward Time-Stepping (FBTS) to apply on microwave imaging for brain tumors.

For colormap design and selection, it has received attention over recent decades. In the early nineties, Bergman et al. explored a rule-based tool to help choose the best colormap for isomorphic, segmentation, and highlighting tasks [47]. Schulze-Wollgast et al. exploited an enhanced automatic color-coding framework by encapsulating metadata extraction, colormap adaptation, and color legend creation [9]. Tominski et al. developed a color-coding function to choose color scales according to particular tasks [48]. Similarly, Mittelstädt et al. [49] proposed a guided tool for selecting suitable colormaps for combined analysis tasks. By conducting several hands-on crowdsourcing experiments with appropriate participants, Reda et al. [50] designed a guideline which indicates that the rainbow scheme or diverging colormaps afford superior accuracy for tasks requiring gradient perception. Likewise, Turton et al. [51] also leveraged a crowdsourced tool called *Ware color key* to assess various colormaps. Also, many research has been focusing on the intersection amid colors, affect, cognition, and behavior [52, 53]. Wilms et al. [54] state that the effect of a certain color on emotions depends not on only a single property but on a combination of them, such as hue, saturation, and brightness. In a similar fashion, Bartram et al. [27] concluded that colormaps have affective expression, inspecting the relationship between affect and color properties (hue, chroma, and lightness) and confirmed the most advisable palette composition design principles with regard to the corresponding emotions. Some affective color-mapping rules were developed by Yang et al. [28] to encode visual properties of colormaps with the valence-arousal model for re-rendering in animation. In practical application settings, the valence-arousal emotion model is widely adopted due to its functionality. Kragel et al. [55] utilized this model to embody complex affect on humans and have constructed a comprehensive emotion-estimating framework in visual systems.

3 Problem solving

As mentioned before, the work outlined in this thesis intends to facilitate the domain related users' cognition for the specialized tomography-controlled processes, by means of accentuating visual comprehension. This chapter specifically introduce the problem solving procedure based on summarizing the methodologies used in the attached papers. For the ongoing confined process, we develop intelligent algorithms by using the IR images to create a see-through pipeline for real-time monitoring. To fully understand the outputted tomographic images, an automatic MWT image segmentation algorithm is proposed to visualize the desired area for users to gain deeper insights. After that, a human-centered design guideline for selecting proper colormaps is brought forward to enhance the users' visual comprehension in the same context.

3.1 Real-time condition monitoring

Paper paper I investigates the advanced feature learning 1.2.1 in improving the monitoring accuracy for a confined microwave drying process through the immediate genetated IR images. The data used comes from three distinct drying processes of different foams with different drying duration. In our experimental setting, IR videos recorded the entire drying process, from the foam being sent into the chamber to its reemergence. We obtained nearly 10000 IR images to store in our dataset. For further support of our observations, we divided the whole dataset into a training set and a testing set, at a proportion of 8:2. There are 8 defined conditions which describe the whole process. Among them, conditions 7 and 8 are recognized as faults if detected.

Method: 4 benchmark neural networks (feature learning, 1.2.1) and 4 baseline models are chosen to implement the training processes to predict the immediate conditions, as well as to find the faults. The 4 benchmark networks (feature engineering, 1.2.1) are one deep convolutional neural network, two transfer learning models, and one deep residual neural network [56], which the 4 baseline models include basic logistic regression [57], naive Bayes [58], support vector machine [59], and linear discriminant analysis [60].

Result: Accuracy is chosen as the metric for evaluating condition monitoring. This widely-used criterion specifies the rate between the samples correctly classified and the total samples in the dataset. From the statistics, we witness how the four feature learning methods completely outstrip the four conventional

feature engineering methods, based on their superior accuracy acquired both in the training and testing phases. Deep learning is thus observed to have satisfactory efficiency in analysing the IR images from the monitoring of this process, supporting the research question proposed in 1.3.1. In training results, it is noteworthy that all four benchmark networks achieve higher accuracy (nearly 100%) when compared to the other four baseline models. Likewise, the feature learning-based benchmark networks outperform the baseline models comprehensively in the testing stage. Our research also shows that transfer learning and deep residual network do not have greater abilities in condition monitoring and prognostic fault detection within a confined microwave drying process. In fact, neither transfer learning networks nor deep residual networks can be shown to have similar training and testing accuracy when compared to our general CNN model in three distinct processes.

3.2 Automatic segmentation for MWT

Method: At the beginning, we conduct a prior study to segment MWT images by two already well-established algorithms: Otsu algorithm [38] and K-means algorithm [61]. We demonstrate that K-means exceeds Otsu in our context from the conventional methods'perspective. The K-means algorithm is a method of cluster analysis in data mining [61] which can also be used in image segmentation. This genre of unsupervised machine learning algorithm aims to minimize the sum of squared distances between all points and the cluster center [62, 63]. This is the one of the simplest clustering algorithms and is computationally faster than the hierarchical clustering. As a type of unsupervised learning, it is widely used in the realm of image segmentation due to its simplicity and efficiency. Many researchers have tried to combine it with other techniques to increase its performance, such as integrating with fuzzy c-means algorithms [40] and partial stretching enhancement [3]. Following such a strategy of combination, our proposed algorithm–MWT Segmentation based on K-means (MWTS-KM)–is established based on the basic K-means algorithm. It integrates image augmentation, grayscale image conversion and conventional K-means into our proposed automatic algorithm. This integrative strategy of our method is derived after considerable and objective test cases.

Result: We conduct segmentation in all the 30 images gained from different microwave drying processes. In our analysis, the segmentation task is a binary classification to distinguish the foreground and the background in images. Accordingly, we intend to categorize our MWT image into two parts; low moisture area and other area. The whole segmentation period for 30 images lasts around three hours. We run all the python scripts in the full-fledged IDE–Jupyter Notebook. The results show that there is almost no evident difference observed between the segmentation results from Otsu and K-means algorithms, both of which are inef-

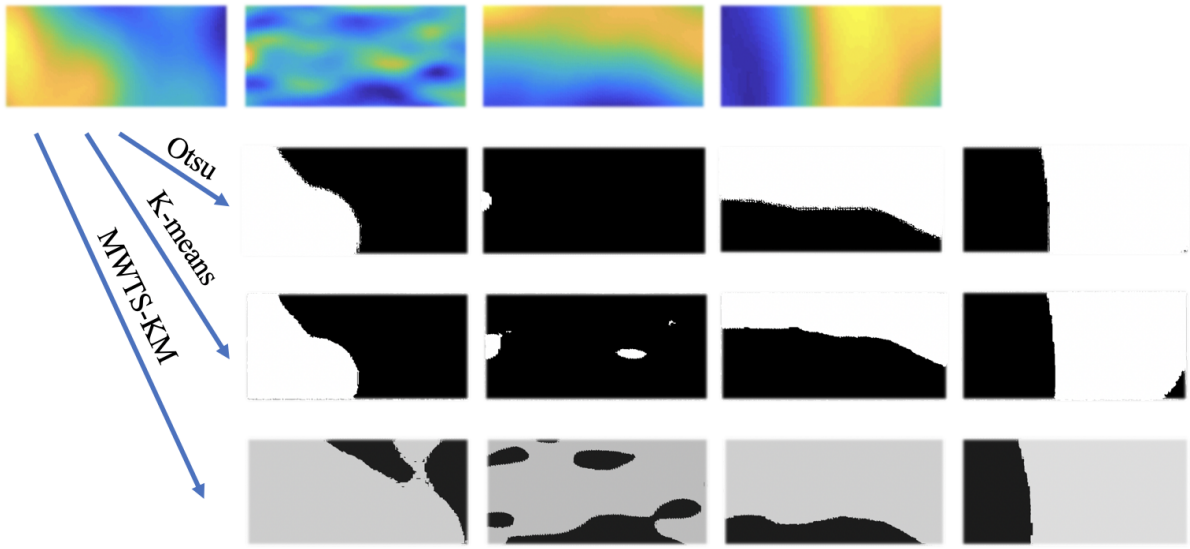

Figure 3.1: *The comparison among three segmentation results. The first row shows the input images. The second row results from applying the Otsu algorithm on the input images. The third row results from using conventional K-means Algorithm while the last row shows output images from the MWTS-KM algorithm.*

fective in obtaining desirable consequences. However, compared to ground-truth images which are input MWT images, our proposed MWTS-KM achieves excellent accuracy in visualizing low moisture areas in terms of perception, as revealed in Figure 3.1. To validate the efficacy, we provide another more convincing quantitative evaluation. The evaluation output for the 30 samples are conducted by Jaccard index, Dice coefficient and false positive. In terms of performance of each algorithm, MWTS-KM exceeds Otsu and K-means remarkably in each metric.

3.3 Colormaps with affect

Method: To answer RQ1 (1.2.3) inculded in paper paper IV, we choose another 10 commonly-used continuous colormaps (listed and elaborated in Figure 3.2) after conducting a literature review. Following the selection, we convert our eight MWT images with the 11 chosen colormaps (we obtained a total of 88 MWT images) by using OpenCV [1]. Thus, we are able to observe each colormap in segmenting the desired low moisture areas (blue parts on the images in parula colormap, which is the original and default colormap).With this implementation, we established the underlying quality of the selected 11 colormaps in the context of the MWT segmentation task. We then executed the same segmentation among all 88 MWT images. The segmentation of each image was conducted by

[1] Open Source Computer Vision Library, referred as a library comprising various programming functions aiming for real-time computer vision: https://opencv.org

Colormap		Hues	Lightness	Design Strategy
parula		multiple	-	**default** (MATLAB)
viridis		multiple	lightness increases monotonically	**sequential** (perceptually uniform)
magma		multiple	lightness increases monotonically	**sequential** (perceptually uniform)
greys		single	lightness increases monotonically	**sequential**
blues		single	lightness increases monotonically	**sequential**
cool		two	lightness function has plateau	**sequential**
autumn		multiple	lightness function has plateau	**sequential**
hot		multiple	lightness function has kinks	**sequential**
copper		two	lightness function has kinks	**sequential**
spectral		multiple	lightness increases and decreases monotonically	**diverging**
coolwarm		two	lightness increases and decreases monotonically	**diverging**

Figure 3.2: *The 11 colormaps we studied with their hues and lightness characteristics, followed by each colormap's underlying design strategy.*

MWTS-KM (3.2) while the overall evaluation for those designated colormaps was accomplished by adopting the same data-driven approach (3.2). The three indexes (Jaccard index, Dice coefficient, and false positive) [64] were used to measure and evaluate the 11 tested colormaps with the segmentation task in paper paper IV.

According to our hypothesis and RQ2 (1.2.3), we intend to test whether those colormaps triggering affect in the positive-exciting quadrant can facilitate more accurate visual comprehension towards MWT than that from the other three quadrants in valence-arousal coordinate system. We designed a crowdsourced user study to verify our speculation. This experiment had two goals, first to examine all the participants'affective responses to the 11 selected colormaps. The emotions from participants were encoded with this circumplex model for further analysis. Second, the user study would test participants'comprehension ability in comparing and rating the accuracy of diverse colormaps from the segmentation task in the prior quantitative evaluation. Hence, our study was divided into two parts. An online questionnaire comprising two parts (I and II) to execute the crowdsourced study is created via Google Forms. The participants are requested to complete the study individually with no time limit. Answers are anynomized for privacy. With no colorblind participants, all results are deemed valid.

Result: Regarding the resolution of RQ1 (1.2.3), we note that in both Jaccard index and Dice coefficient, autumn scheme reaches very a high value, even approaching 1.0 in some cases, which demonstrates excellent performance. Similarly, it yields considerably low false positive assessment over the whole samples. Colormaps viridis and parula obtain brilliant performance consistently among the three metrics assessment. Then we note that colormaps spectral, coolwarm, and

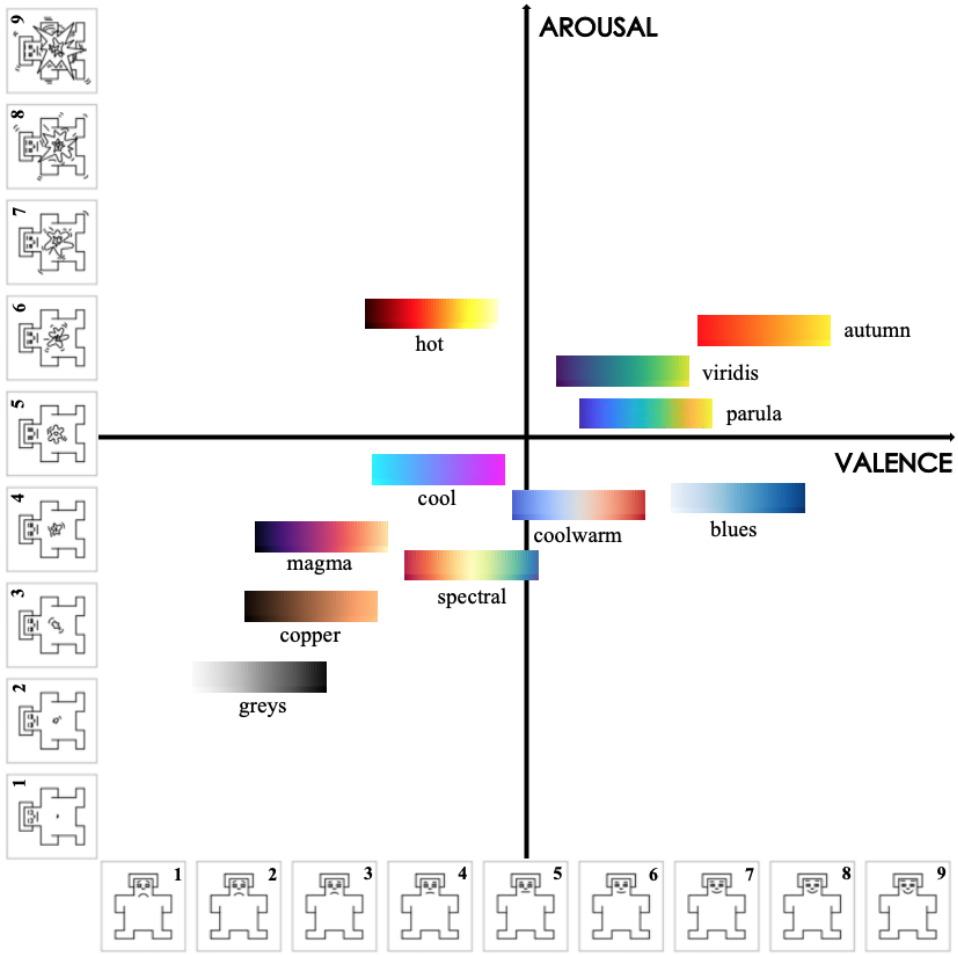

Figure 3.3: *The synthetic distribution of the 11 colomaps regarding the affect evoked in the valence-arousal coordinate system.*

magma have the low evaluation outcomes (low Jaccard index and Dice coefficient values but high false positive values) corresponding to initial results (In Figure 3, those 3 colormaps are not able to visualize the blue parts correctly). By combining the complete results, it is fair to conclude that autumn, viridis, and parula schemes appear to be the most desirable choices.

Regarding the results from the crowdsourced user study which is for RQ2 (1.2.3), the outcomes support our hypothesis firmly. The first part of the user study is to encode the affect caused by the 11 chosen colormaps, both in valence and arousal dimensions. From our aggregated data acquired from the results and the visualized plots (Figure 3.3), it is fair to conclude that colormaps parula, viridis, and autumn trigger emotions mostly in the positive-exciting quadrant. Conversely, coolwarm, spectral, magma, greys, copper, and cool incite the affect mainly in the negative-calm quadrant. The remaining colormaps blues and hot are in the positive-calm and negative-exciting quadrants respectively. Secondly, another part of the user study records the rating of the accuracy of each colormap

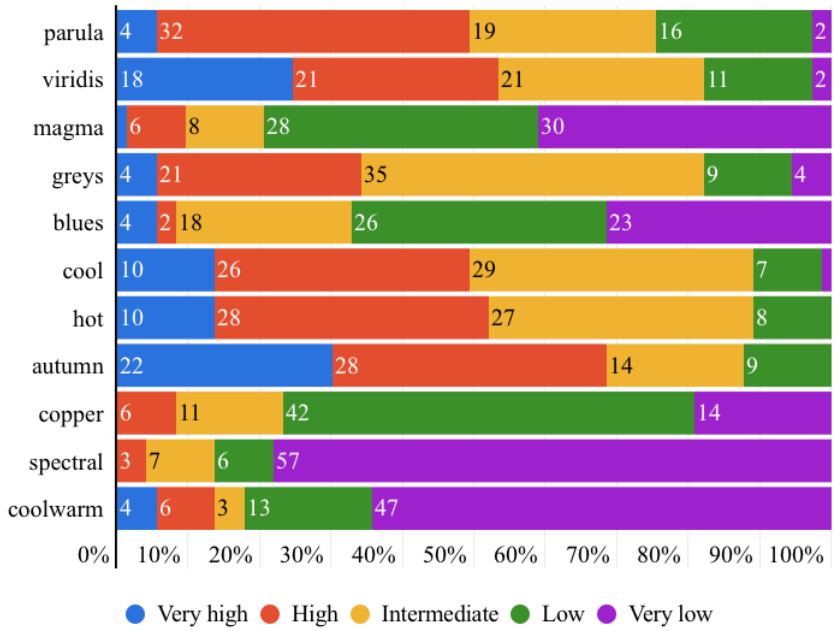

Figure 3.4: *The overall accuracy rating results of the 11 colormaps by the 73 participants (rating scale: very high accuracy, high accuracy, intermediate accuracy, low accuracy, and very low accuracy).*

on the same segmentation task by the participants who use their own comprehension (Figure 3.4). By observing the entire results, it is fair to initially conclude that the colormaps autumn, viridis, parula, hot, and cool are favored over spectral, coolwarm, magma, copper, and blues. After combining the two parts of the croedsourced study, we can thus confidently conclude that the color schemes autumn, viridis, and parula are the most desirable results from the judgement by human visual comprehension, while spectral, coolwarm, and magma schemes are much less preferable in the same context.

4 Discussions

Enhancing human vision to improve the visual comprehension towards tomography-controlled industrial processes is the main point discussed in this thesis. In this chapter, the insights obtained with the limitation spotted are illustrated.

4.1 Deep learning for real-time condition monitoring

Paper paper I shows that the state-of-the-art feature learning-based tool, CNN and its variants, are advantageous for condition monitoring in a confined microwave drying process by using IR images. The merit of feature learning is that it conducts iterative feature transformation, which conventional feature engineering does not have, making the implementation more reliable. In addition, we also verify that transfer learning and deep residual neural networks do not outperform the standard CNN model. Overall, feature learning-based methods are well-qualified to provide robust monitoring in various conditions and to detect faults in a non-visible microwave drying process, as shown in our three distinct demonstrations. Deep learning transcends traditional condition monitoring methods by a range varying from approximately 3% to 48%, according to our research.

However, there is still room to advance our approaches in Paper paper I. First, the volume of the database should be enlarged to more closely approximate the massive database that would be required for truly analogous research. In addition, the thickness, as well as other physical properties, of the foam chosen in the experiment may affect the temperature distribution, which may influence the desired results. To make the research more robust, a greater variety should now be tested.

4.2 MWTS-KM automatic segmentation

To summarize paper paper II, we implement image segmentation technology in 30 MWT images obtained from the specialized microwave drying processes. The proposed MWTS-KM algorithm is applied to segment images to visualize the areas indicating low moisture level for porous foams in relevant context. We compare MWTS-KM with another two commonly used methods and appraise them thoroughly. K-means algorithm surpasses Otsu in general cases even though there is only a moderate difference between them. In some samples, the Otsu algorithm

is superior to K-means algorithm whereas it is disadvantageous compared to K-means algorithm. However, Our proposed algorithm has the highest Jaccard indexes and Dice coefficients with the lowest false positive values as a tremendously acceptable result. On the other hand, there still are some inefficiencies in our algorithm, such as inadequate samples and lack of more complete pre-processing steps.

4.3 Affective colormap design

What do we obtain from all the results acquired in paper paper IV? Foremost, we propose two core research questions (1.2.3) regarding our study. How can various colormaps affect task accuracy in the context of MWT so as to impart accurate visual comprehension? Are the colormaps triggering human affect in the positive-exciting quadrant in the valence-arousal grid able to facilitate more accurate visual comprehension in terms of human perception towards MWT than those from the other three quadrants? To resolve our RQ1 (1.2.3), we carry out a metric-driven quantitative evaluation to judge the performance of individual colormaps based on the same segmentation task. After consulting relevant literature, we selected 10 prevalent continuous colormaps (plus a default colormap, totalling 11 colormaps tested) which were capable of retaining the needed information in MWT images. By means of an automatic segmentation approach, we then obtain the easily-distinguishable results which enabled us to determine the most appropriate colormaps. We find that color schemes autumn, viridis, and parula were considered the optimal options in comprehension-based scientific analysis of MWT. In addition, we conclude that the colormaps spectral, coolwarm, and magma were undesirable in the same context.

More critically, inspired by well-proven research on colormaps-emotion, paper paper IV reflects on a comprehensive crowdsourced user study to address RQ2 (1.2.3), as well as to validate our hypothesis. A 73-participant involved study is formalized to verify whether the advisable colormaps concluded from the quantitative evaluation are encoded in the positive-exciting quadrant in our built valence-arousal model. We divide the whole study into two parts. Part I collects the affect of how participants react to the 11 different testing colormaps and recorded the outcomes. In Part II, our complementary study investigate the ratings by the participants of the segmentation accuracy of each colormap. Through integrating the two parts, we expectedly find that the most desirable colormaps autumn, viridis, and parula indeed trigger the human affect in the positive-exciting quadrant which conforms with our hypothesis.

The first limitation manifests in paper paper IV is that we investigate 11 different colormaps in terms of several selection strategies, in which categories (sequential and diverging) and color properties (hues and lightness) were considered. However, the design strategy of additional colormaps could be enriched by adding

more classes of colormaps that might then give similar or more outstanding performance in our context. Second, we chose continuous colormaps simply because of their ability to retain complete information of MWT as well as respecting the default setting in MATLAB. However, the scope could be extended by inspecting discrete colormaps. Last but not least, some factors influencing the crowdsourced study could not be controlled. For instance, we recruit participants from a range of domains while the working environment of each participant could not be controlled. Participants most likely are subject to different screen resolution, lighting, and other environmental factors. A unified and subjective working environment could have ensured more robust results.

5 Conclusions

Some industrial processes take place in confined settings only observable by sensors, e.g. infrared (IR) cameras. Paper paper I focuses on a drying process being taken place in an isolated chamber while a material is transported by means of a conveyor through a 'black box'equipped with internal IR cameras. Inspired by numerous implementations monitoring techniques that analyse IR images using deep learning, this work shows how they can be applied to the confined microwave drying of porous foams, with benchmarking their effectiveness at condition monitoring to conduct fault detection. Our comparison shows that state-of-the-art deep learning techniques significantly benefit condition monitoring, providing an increase in fault finding accuracy of up to 48% over conventional methods. Nevertheless, we also find that derived transfer learning and deep residual network techniques do not in our case yield increased performance over normal convolutional neural networks.

After a complete microwave drying process, it is critical for domain related users to understand the output, which is the reconstructed tomographic images. Hence, paper paper II contributes to the development of an automatic MWT segmentation algorithm to visualize the desired areas representing important information. Firstly, we prove the mature segmentation methods which have been widely used in tomographic systems are considerably suitable for MWT image segmentation. In our study, this technique is an intuitive and innovative method for visualizing the low moisture areas of foams. We have developed an entirely automatic methodology named MWTS-KM to conduct the MWT image segmentation, validating its high efficiency and high accuracy after practical experiments. This method is able to meticulously visualize the low moisture areas for foams in MWT images. Furthermore, its performance is superior to two other preeminent methods.

To better promote human comprehension among the reconstructed MWT image, we set up a colormap deisgn research in paper paper IV based on the same segmentation task as in paper paper II. A quantitative evaluation of our work shows that different colormaps can influence the task accuracy in MWT related analytics, and that schemes autumn, virids, and parula can provide the best performance. In our systematic crowdsourced study, we verify our hypothesis that the colormaps triggering affect in the positive-exciting quadrant in the valence-arousal model are able to facilitate more precise visual comprehension in MWT than the other three quadrants. Interestingly, we also discover the converse-finding

that colormaps resulting in affect in the negative-calm quadrant are undesirable. Therefore, we propose a synthetic design guideline for future practitioners to select colormaps boosting accurate visual comprehension in the context of MWT.

From the perspective of HCI, it is vital to make humans, such as domain related users or operators, to become aware of the various industrial processes. As the thesis title resembles, benefiting human vision is plays an important role in this context. We have used the IR images describing the ongoing processes for real-time monitoring as well as enabling users to find the faults immediately. Then, we develop an automatic segmentation method for outputted MWT images to visualize the needed part, which allows people to visually understand the data better. Finally, through a systematic colormap design with human affect, we have successfully obtained the most suitable color schemes which are capable to facilitate accurate visual comprehension in the context of industrial tomography.

6 Future work

The research contained in this thesis is novel and has various possibilities in relevant future studies. It tackles problems in order to benefit humans, while engaging many intelligent methods such as machine learning (ML) /AI. As a popular topic, ML has been pervasively used in a variety of applications to obtain the better results. In terms of HCI, to make ML beneficial for humans is an interesting realm. In future work, we will concentrate on human-centered machine learning (HCML), which is an emerging subfield of computer science which combines the expertise of data-driven ML with the domain knowledge of HCI. ML research works on pre-existing, well-standardized datasets, using objective measures such as accuracy, precision, while HCI works directly with people, using qualitative or quantitative user studies. In HCML, it emphasizes the deployment of human-centered approaches to the conception, design, implementation, and evaluation of ML systems. The targets of HCML are utilizing human-centered practices to make ML systems more usable and reliable, and eliciting deeper understanding of human contexts that leads to ML systems that have greater impact and comprehensibility in terms of human concerns.

We will focus on this novel interdisciplinary research field to support developing the real-time industrial decision-support system. In our context, we are supposed to obtain the appropriate real-time decisions through relevant data collection, modelling, evaluation, and determination, which is subject to effective ML systems. However, the information regarding the whole process should be easily-perceivable, highly-understandable to the people involved in this loop. That is, it's critical to take the users needs, goals, behaviors, and constraints into account so as to design human-centric interactive ML systems, benefiting both human concerns and the objective data-driven predictions. To efficiently concretize the procedure, we are able to roughly organize our potential work into three stages:

- Collect the needs, goals, behaviors, and constraints of the context related users, in a sustainable efficient manner. Use methods of ethnography and contextual research to understand the problem space. Find out the status and prospects of the use of ML in context related users. Propose a design framework (can be an object, interface, system, or service) to effectively address the needs found, which is used for further development of interactive ML systems (note: domain users).

- Develop an interactive ML system to support accurate decision-making,

which possesses high usability leading to great human perceivability and comprehensibility.

- Create the whole framework of the real-time decision making system for the designated context. It should include the effective tool to model human concerns and the progressed interactive ML system which gives precise predictions and the great impact on humans.

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