https://doi.org/10.2352/EI.2023.35.1.VDA-403

Visualizing and Monitoring the Process of Injection Molding

Christian A. Steinparz [1], Thomas Mitterlehner [3], Bernhard Praher[3], Klaus Straka[2,3], Holger Stitz [1,4], Marc Streit [1]

[1] *Visual Data Science Lab, Johannes Kepler University, Linz, Austria*
[2] *IPIM, Johannes Kepler University, Linz, Austria*
[3] *Moldsonics GmbH, Linz, Austria*
[4] *datavisyn GmbH, Linz, Austria*

Abstract

In injection molding machines the molds are rarely equipped with sensor systems. The availability of non-invasive ultrasound-based in-mold sensors provides better means for guiding operators of injection molding machines throughout the production process. However, existing visualizations are mostly limited to plots of temperature and pressure over time. In this work, we present the result of a design study created in collaboration with domain experts. The resulting prototypical application uses real-world data taken from live ultrasound sensor measurements for injection molding cavities captured over multiple cycles during the injection process. Our contribution includes a definition of tasks for setting up and monitoring the machines during the process, and the corresponding web-based visual analysis tool addressing these tasks. The interface consists of a multi-view display with various levels of data aggregation that is updated live for newly streamed data of ongoing injection cycles.

Introduction

Injection molding is an important manufacturing process in polymer processing for producing components for a variety of markets, including the automobile industry, medical engineering, and the electronics industry [23]. The resulting products range from screw caps to car bumpers [7] and degradable screws for broken bone restoration [5]. The domain is characterized by increasing requirements regarding various quality properties and the reduction of rejects, leading to a rise in the need for zero defect manufacturing, automated optimization, and the reduction of production times. In this work, we focus on assisting machine operators in performing tasks in both the **setup phase** of the molding machines and the **monitoring phase** of the overall production. These tasks are mostly driven by errors in the filling process. This work is the result of a collaboration with domain experts who specialize in the development of non-invasive ultrasound-based in-mold sensors and the measurement process [21]. Together we elicited a series of domain-specific tasks which are essential to the process and persistent in the domain, for which they provide real data. To the best of our knowledge, there are currently no solutions available that address these tasks. Existing solutions are often limited to encodings such as individual time series plots with limited to no interactivity [6], or are designed for analyzing overall production cycles [17]. Domain experts require live analysis capabilities of ultrasound measurement data from the injection process being streamed to a tool in which the visual encodings and interactions are tailored to their specific tasks. In our design process, we iteratively refined our shared understanding of the problem, the tasks, and the visual design. Our main contribution is an interactive visualization tool to assist injection molding machine operators. In addition, we formulated a set of tasks that emerged from this collaborative process, which are defined in the following.

Background and Tasks

An injection molding machine injects molten material into a **mold** which consists of at least one negative form called **cavity**. To increase the output, multiple cavities are being filled simultaneously, before undergoing additional phases such as holding and cooling. After the resulting components are ejected, the process is repeated over multiple iterations called **cycles**. The measurement of this forming process and usage of the resulting data remains a rare occurrence, as the molds are typically built without any connected sensors [15], and due to the fact that in-mold sensors need to withstand high pressures and temperatures [21].

The data to be visualized consists of ultrasound measurements over time from which an **intensity** is calculated as the integral of the absolute amplitude. The domain experts break the ultrasound measurements into the first three semi-oscillations called **main pulse** and the **post-oscillation** (see Fig. 2). Typical problems in this procedure include the prevention of overfilling of a cavity, referred to as **flashing**, and respectively underfilling, referred to as **short shot** (see Fig. 3-c), as well as the efficient setup and monitoring of the process. The design with which we address these challenges is based on a comparison to **reference data** of defect-free injection processes. We further decompose and concretize these problems such that they can be efficiently solved via visual analysis. As a result, we present the following set of detailed tasks which need to be supported by the tool, where T 1 through 6 are derived from the main pulse and T 7 from the post-oscillation. The tasks are split into two process phases: the **setup phase**, in which the operator configures the molding process to result in high-quality products, and the follow-up **monitoring phase** in which the operator needs to ensure constant output quality. The user of the visualization guiding this process and the machine operator may be two separate individuals.

- **T 1: Recognize problems during the filling process.** Users need to be able to recognize the occurrence of flashing or short shot for each cavity.
- **T 2: Optimize the holding pressure time.** Users need to be able to recognize deviations in the sealing point (see Fig. 3-b) after which no more material can be injected, allowing

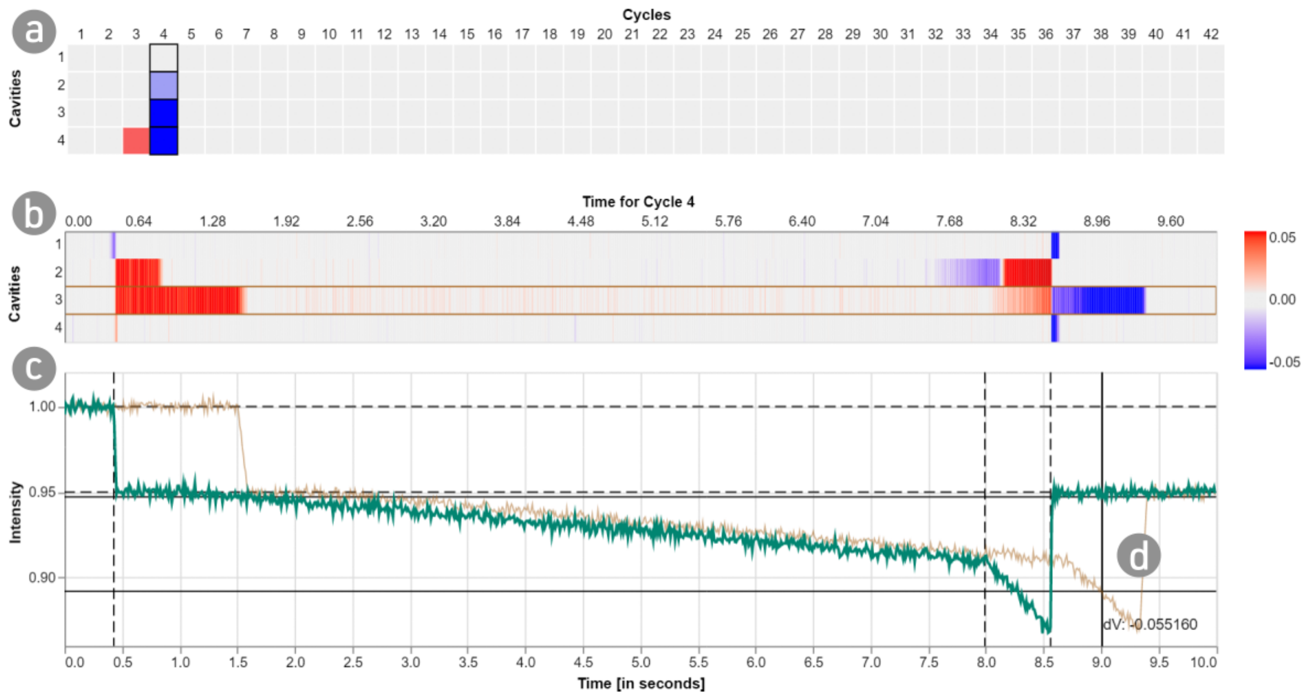

Figure 1. *Interactive multi-view display for various levels of aggregation in the visualization injection molding processes. (a) The validation heatmap (VHM) displays the short shot (blue) and flashing (red) of cavities of the molding tool over multiple cycles streamed live to the visualization. (b) The progression heatmap (PHM) explicitly encodes the difference in ultrasound sensor intensities of selected cycles/cavities to a selected reference. (c) The time series plot (TSP) shows the reference curve (green) superimposed to other selected measurements (yellow), with additional annotated metadata (dashed lines). (d) Users can view detailed comparisons to the reference by placing crosshairs (solid lines).*

for the optimization of the holding pressure time.

- **T 3: Minimize cooling duration.** Users should be able to check and compare the shrinkage-lift-time (see Fig. 3-b) when the component loses contact with the cavity wall due to shrinkage, as this allows for the minimization of the cooling duration. For large components and multiple sensors, users can then use this information to compare cooling conditions among different measurement positions.
- **T 4: Check the duration and consistency of the filling.** Users need to be shown the detection time for the area between melt and air (flow-front, see Fig. 3-b) and infer the consistency of filling. When using similar cavities users can then verify the regularity among them.
- **T 5: Check whether the process is thermally stable.** Users need to be able to recognize deviations in mold temperatures by comparing start-intensities before injection and end-intensities before the shrinkage-lift-time (see Fig. 3-b), given that the main pulse intensity is dependent on the temperature (see Fig. 3-a).
- **T 6: Recognize whether the overall process is stable.** To recognize whether the cavity status is acceptable, also in cases where many cavities are displayed at the same time, users need to be able to compare measurements to reference data.
- **T 7: Infer the consistency of the frozen layer growth rate for post-oscillation data.** Users need to be able to check the minima and maxima of the post-oscillation intensity (see Fig. 4) for monitoring after the process setup, as this allows to infer the consistency of the freezing duration of the melt.
- **T 8: Continuous monitoring of new cycles.** New data streamed to the tool needs to be added to the visualization automatically.

Related Work

The domain problem at hand deals with the visual analysis of dynamic temporal data, as characterized by Aigner et al. [2]. This data consists of a combination of the internal time of measurements and an external time given by the streaming of new cycles. This difference between internal and external time poses a challenge for designing effective visualization solutions. We address this problem by allowing users to interact with multiple levels of data aggregation in a multi-view display. Dasgupta et al. [9] discuss streaming data analysis, including machine-level and human-centered challenges. Following their characterization, we employ spatial encoding of age via juxtaposition in heatmaps without sub-sampling, we archive old data via scrolling and apply superimposition of user-selected cycles in a time series plot. Gleicher [12] introduces a framework for choosing visual encodings that support the comparison of data, which fits our comparison of fill status and intensities to selectable reference curves. In addition to the design elements juxtaposition and superimposition, Gleicher mentions explicit difference encodings which we utilize as well.

In the context of injection molding, a large body of work exists towards the hardware aspects and non-invasive measurements during the running process, for instance, regarding the use of ul-

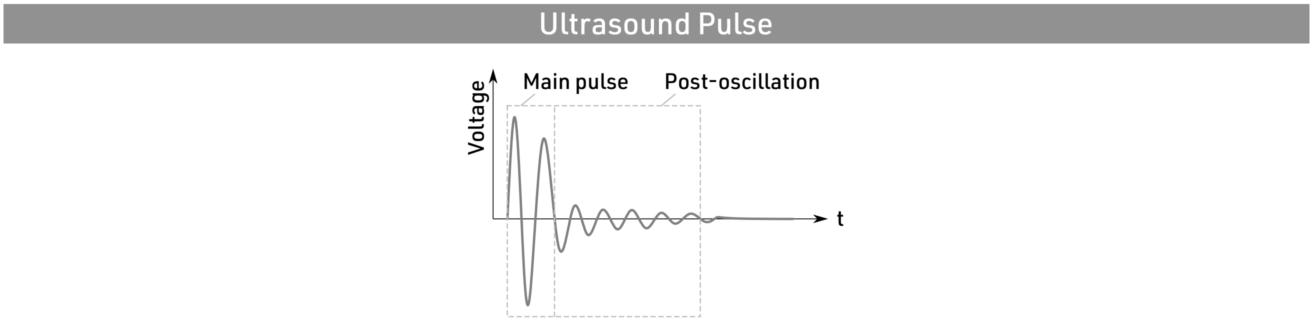

Figure 2. *Schematic depiction of the ultrasound measurement and how it is divided into the main pulse and the post-oscillation. From this signal, the intensity is calculated as the integral of the absolute amplitude.*

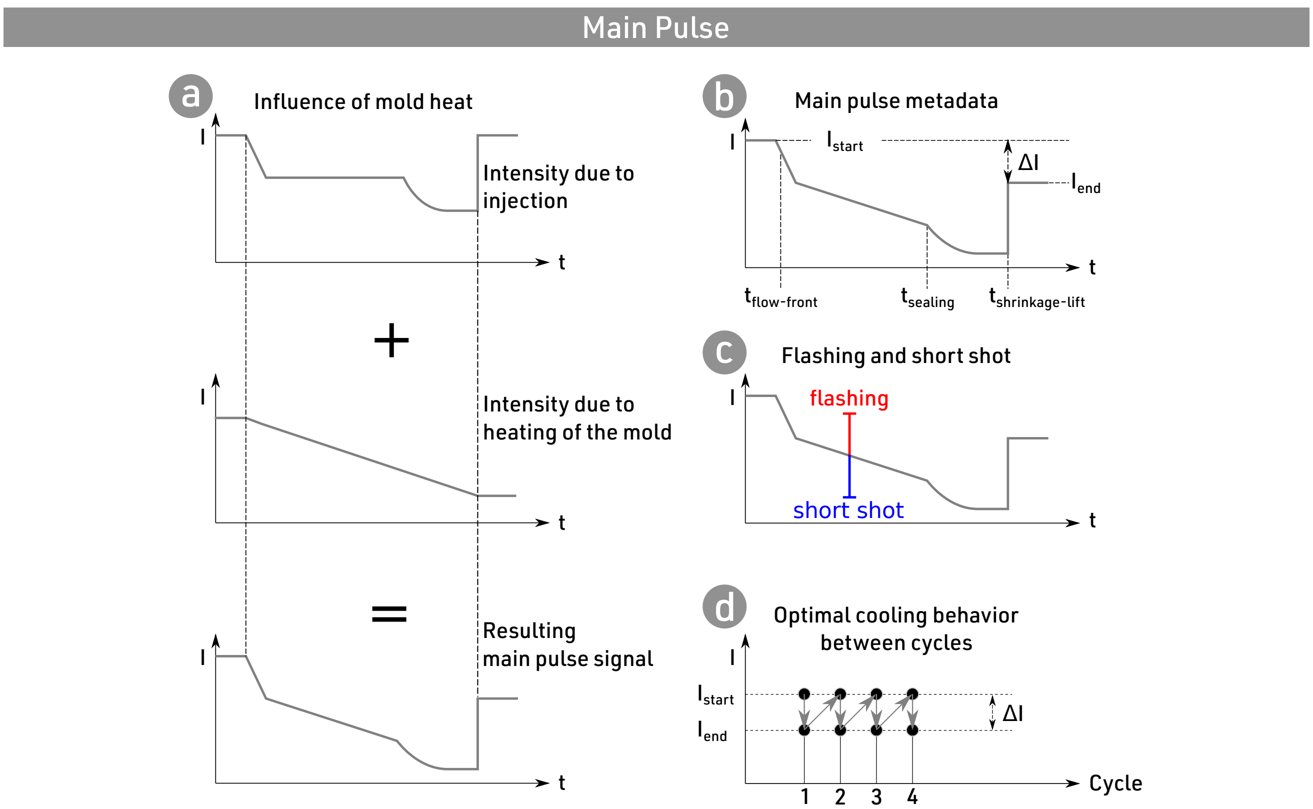

Figure 3. *Schematic depiction of the main pulse. (a) The main pulse is a result of intensity deviations caused by the injection and the heating of the mold. (b) Metadata for the main pulse that is relevant for the user tasks. (c) Overfilling (flashing) and underfilling (short shot) of a cavity. (d) Thermally stable process in which intensity deviations due to heating of the mold are constant over subsequent cycles.*

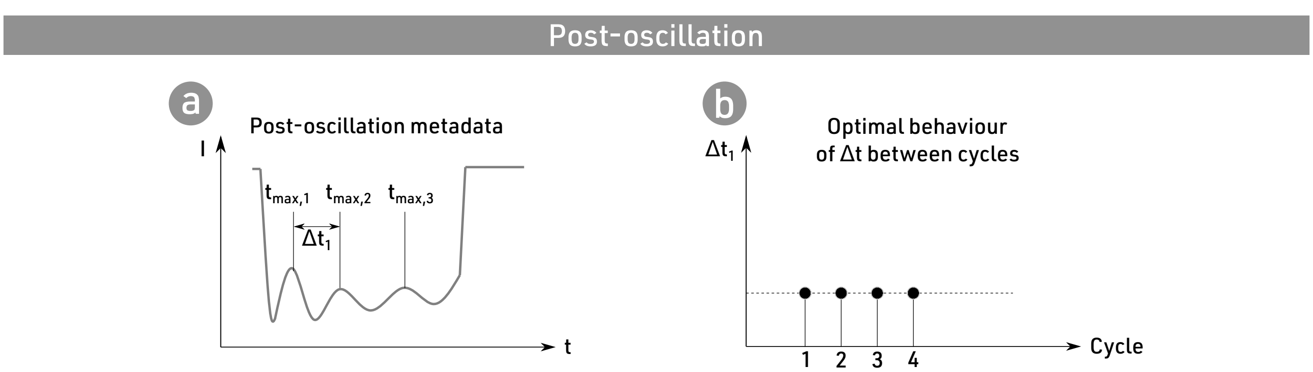

Figure 4. *Schematic depiction of the post-oscillation. (a) Metadata for the post-oscillation consists of the time of the maxima of the oscillations. (b) Optimal behavior for one cavity in which the intervals between maxima are constant over subsequent cycles.*

trasound sensors [4, 20, 1, 16]. Visualizations have been proposed for simulating the material flow during the injection molding process [10, 13], or for analyzing the mechanisms behind injection molding based on imaging data [14, 25, 11]. The visualization capabilities of state-of-the-art injection molding monitoring tools, such as ComoNeo [18] and Cavity Eye [6], are limited to time series plots and bar charts that often do not support direct interaction and are not interlinked. The same applies to more general tools, such as ibaInCycle [17] or TIG [24], that cover the whole manufacturing process ranging from order management to process monitoring and quality assurance. An exception seems to be the proprietary Greiner BigDataVis tool mentioned in the state-of-the-art report on visualizations in industrial processes by Cibulski et al. [8]. However, there is no public information available describing the tool in more detail. Very closely related to our work is the approach by Musleh et al. [19] who create a visualization for blow molding machines. In contrast to injection molding where solid parts like plates or discs are formed, blow molding is similar to glass blowing and used to create singular hollow objects such as bottles. Musleh et al. make use of multivariate time series data and focus on extracting important features from the data using machine learning. This is part of an iterative design process in which they create a web-based visualization comprised of several visual representations. The resulting tool is used to assist the decision making process of the respective domain experts.

Data Abstraction

When discussing the tabular measurement data we refer to rows as samples and columns as features. Any additional features other than intensity and time will be referred to as metadata. Our collaborators provided real-world data from an injection molding machine that has the novel ultrasound sensors installed. The data was partly extrapolated and modified to identify scalability issues and test corner cases.

Data Format

As illustrated in Fig. 5, each sample consists of the features cycle number, cavity number, intensity, measurement time, and fill status (-1 for short shot, 0 for defect-free, +1 for flashing). These are followed by additional metadata flags (0 or 1), which we depict in Fig. 3-b and Fig. 4-a. For main pulse data, these flags are sealing point, shrinkage-lift-time, flow-front-detection-time, start-intensity, and end-intensity. For post-oscillation they are the first minimum, the second minimum, shrinkage-lift-time, flow-front-detection-time, start-intensity, and end-intensity.

Data Design Process

The data abstraction is a result of the iterative design of visualization possibilities and emerging tasks, the requirements for which can be easily satisfied in this data format, and provided without much overhead by the machines. The metadata is encoded for each sample individually, can be reported by the machine, and except for cycle and cavity numbers could occur in the data multiple times per cycle-cavity pair. We choose to encode these as per-sample metadata as it is sufficient for the visual encoding, and requires hardly any implementation overhead for the domain experts.

Method

The iterative design process resulted in an interactive multi-coordinated view setup consisting of three components that support different levels of aggregation, and provide assistance for each task (see Fig. 1): (1) the **validation heatmap (VHM)** showing for all cycles and cavities whether flash or short shot is occurring, (2) the **progression heatmap (PHM)** visualizing the intensity difference between selected cycle-cavity pairs and a reference, and (3) a **time-series plot (TSP)** providing access to the detailed measurements with respect to the reference curve. Fig. 5 illustrates how the measurements are taken by the machine and which features are shown on which level in the three connected components.

Validation Heatmap

The VHM (see Fig. 1-a) serves as the top-level abstraction. The x-axis and y-axis of the VHM display cycles and cavities such that the diverging color map shows the average fill status of each cycle-cavity pair. Gray indicates defect-free pairs, red indicates flashing, and blue indicates short shot (supporting task T 1). Users can choose the reference curve from a predefined set using a drop-down menu. Alternatively, the reference curve can be set by selecting a single tile in the VHM. In addition, users can vertically brush over the VHM to select a number of cavities of one cycle that they want to investigate. Similarly, they can horizontally brush over cells to select a number of cycles for one cavity. The heatmap grows horizontally when new cycles are streamed to the visualization (supporting T 8). By selecting cycle-cavity pairs, users can use the PHM and the TSP for addressing the remaining tasks.

Progression Heatmap

The VHM selection adds the selected cycle-cavity pairs to the PHM (see Fig. 1-b). The categorical y-axis displays the cycles (or cavities) after a vertical (or horizontal) VHM brush. The x-axis represents the time of the measurements. The color indicates for each cycle (or cavity) at each time step whether and to what extent the intensity is above, below, or within an acceptable range regarding the reference value, displayed in red, blue, or gray respectively. Within the PHM, users can also select one of the cycles (or cavities). The heatmap especially supports T 6 and assists the TSP with T 2-T 5, and T 7.

Time-Series Plot

The PHM selection allows users to further drill down in the TSP (see Fig. 1-c). The VHM selection initially adds all of the corresponding cycle-cavity pairs to the TSP, while also displaying the reference curve. When users make a selection in the PHM, the TSP shows only the reference and the selected curve. Users can place crosshairs to quantify the difference between the selection and the reference curve (see Fig. 1-d). The first click places a crosshair that displays the intensity difference between reference and selection at the given x-position. The second click adds an additional crosshair on a new x-position for the selected curve displaying the difference to the first reference value. Additionally, the metadata is depicted by vertical dashed lines for timestamps and horizontal dashed lines for intensities. With annotations and crosshairs, the TSP supports T 2-T 5, and T 7.

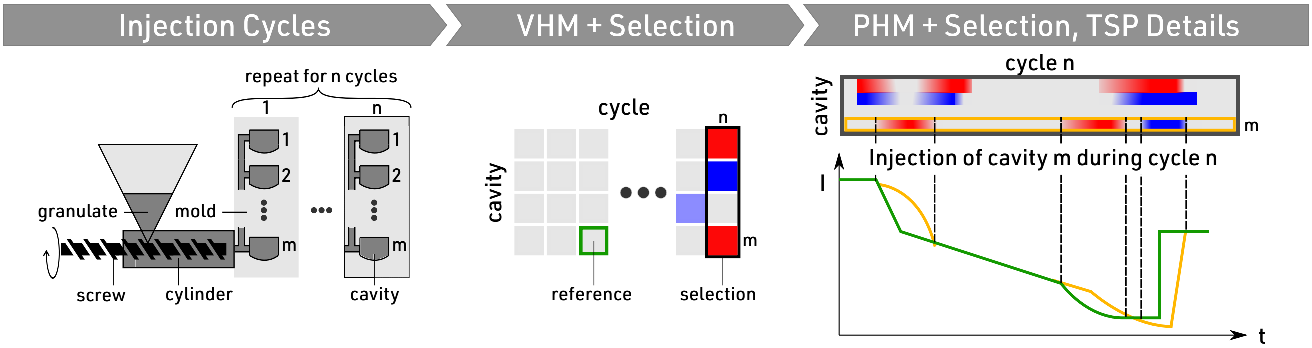

Figure 5. *Workflow for the visualization of the injection molding process. Cavities of a mold are injected over several cycles, potentially resulting in flashing or a short shot. The fill status is displayed in the VHM, with new cycles being streamed to the visualization. A selection of cavities and cycles is displayed in the PHM. By further selection within the PHM users drill down in more detail in the TSP.*

Visualization Design Process

Task Utility Versus Collaborator Familiarity The tasks described above were the main factors that influenced our design decisions regarding the visual encodings and interactions. In addition, we considered the preferences our collaborators had regarding visualizations they are already used to. This iterative design process resulted in a multi-stage concept that supports different levels of aggregation of the same data. The views display the data via different encodings and interactions such as selections, re-using the same axis, and synchronized zoom levels. This approach enables us to simultaneously show visual encodings they are familiar with while offering more utility regarding the user tasks via other encodings. Specifically, we include the TSP given that domain experts are used to line charts with timestamp annotations and crosshair interactions as the standard means to work with the measurements.

Scalability An aggregated overview is necessary as the TSP does not scale to more than 6-8 curves, and the resulting clutter would impose difficulties in perceptually connecting curves to their corresponding cycle and cavity. We, therefore, use the VHM to show short shot and flashing events directly on a high aggregation level. The possibility to then further drill down and select individual curves naturally reduces the problem of clutter in the TSP, and enables users to solve the tasks that require more detail. The VHM also supports the streaming of new data such that new cycles become immediately visible, and are separated from previous ones, by appending them further along the x-axis of the VHM. Moreover, the PHM provides an additional view for the same data shown in the TSP, and they are linked by re-using the same x-axis for the time of measurements. This allows users to see differences to the reference for dozens of cycle-cavity pairs at once, and more with scrolling.

Difference Encoding The PHM allows us to visualize differences to the reference directly, making them immediately visible without having to compare two curves. This also makes it apparent to which cycle and cavity the measurements belong. Since both the VHM and PHM display whether the measurements are below or above the desired value, we use the same diverging color map ranging from blue for a fill status smaller than the reference, over neutral grey for the same status as the reference, and red for a fill status above the reference.

Alternative Designs We considered a parallel coordinates plot as an alternative for visualizing fill status, such that users can read the exact average of short shot or flashing events. However, we decided against the technique because the encoding would impose difficulties on distinguishing cavities due to superimposition. Even further aggregation showing the average fill status of all cavities in a cycle would be too coarse for solving the user tasks. We argue that our PHM encoding is an improvement over the time-series plot, following the considerations by Gleicher [12], who also provides a case study of Sequence Surveyor [3] which employs a similar visual encoding for large amounts of sequences.

Implementation

We select a fitting technology stack and choose Vega-Lite [22] with custom external modifications, running on an Angular web app. The tabular data consists of CSV files, and the live updates containing new CSVs for the visualization are handled via the streaming data functionality of Vega-Lite. A live demo of the tool can be found at:
`https://p2f-moldsonics.caleydoapp.org/`

Usage Scenario

The following usage scenario illustrates how the solution supports users in solving the defined tasks for setting up, fine-tuning, and monitoring the molding process.
The user starts by loading the data source corresponding to the desired machine and mold with the intention of setting up the process for production. After the first molding cycle, the initial cycle-cavity pairs are only displayed in the most aggregated form in the VHM. The user immediately notices that flashing or short shot events are occurring in all but one cavity of cycle 4 (T 1, see Fig. 1-a). In the VHM, the user selects all cavities of the defective cycle 4, thereby displaying the respective data in the PHM and TSP. In order to check them against the desired values for the setup phase, the user selects the appropriate reference curve from the defect-free cavity 1 of the same cycle 4. As a result, the various metadata timestamps of a defect-free cavity are now displayed. By inspecting the PHM the user recognizes where the

other cavities deviate from the reference and to what extent. To get the exact value by which the cavities are deviating, the user selects the corresponding cavities one by one. They then position the crosshair, to display the intensity difference. This way, the user is able to optimize the holding pressure time (T 2) by referencing the sealing point timestamp, optimize the cooling duration (T 3) by referencing the shrinkage-lift-timestamp, and check the duration and consistency of the cavity filling (T 4) by referencing the flow-front-detection-timestamp. By the same means, the user can check the exact difference between start and end intensities indicated by the horizontal dashed lines at their respective y-positions, and infer the thermal stability of the tool (T 5). From the signals described above, the user can also infer the corresponding properties for different cavities of similar make. While checking these values, as well as when no selection is made in the PHM (meaning all curves are displayed in the TSP against the reference), it is also evident from the shapes of the curves whether the overall process is stable (T 6).

After this initial setup phase is completed, the user switches to the process monitoring phase. Additional cycles of the injection molding are performed, and new data is fed live into the visualization and displayed in the VHM (T 8). Finally, the user can switch to a different data source to monitor the post-oscillation, and to observe whether the metadata timestamps, which depict the extrema of the post-oscillation, are evenly distributed (T 7).

Limitations

Currently, the entire interpretation of the data during both the setup and monitoring phases is carried out by the user with no automation. This can be a bottleneck, for instance, when users want to use the crosshairs to determine exact intensity differences rather than relying on the PHM. In this case, curves are compared against the reference one by one. Additional automated analytics, filtering, and predictive tools could further improve this workflow.

Conclusion

This collaboration with injection molding experts allowed us to design an interactive tool for the visualization of the injection molding process. We explained our decision-making process and how it iteratively lead to the refinement of tasks, visual encodings, and data abstractions. The design process resulted in both a tool that can ease the setup and monitoring for machine operators, as well as insights that can pave the way towards further advancements in the area. Our design brings the entire process closer to automatization, as the domain experts state that some of the tasks that were formalized in this design could be executed without a machine operator after further development. One additional factor regarding future improvements is the combination of visualization with automated analytics concerning the collection of potentially interesting behavior and patterns in the process, and the presentation of these together with an explanation to users. This applies to characteristic temporal patterns within the process, but also to effects caused by external influences, that is, predictive maintenance.

Acknowledgments

This project was partly funded by the Moldsonics GmbH.

References

[1] M. Aigner, B. Praher, C. Kneidinger, J. Miethlinger, and G. Steinbichler. Verifying the melting behavior in single-screw plasticization units using a novel simulation model and experimental method. *International Polymer Processing*, 29(5):624–634, 2014.

[2] W. Aigner, S. Miksch, H. Schumann, and C. Tominski. *Visualization of time-oriented data*, volume 1. Springer, 2011.

[3] D. Albers, C. Dewey, and M. Gleicher. Sequence surveyor: Leveraging overview for scalable genomic alignment visualization. *IEEE transactions on visualization and computer graphics*, 17(12):2392–2401, 2011.

[4] D. Altmann, B. Praher, and G. Steinbichler. Simulation of the melting behavior in an injection molding plasticizing unit as measured by pressure and ultrasound measurement technology. In *AIP Conference Proceedings*, volume 2055, page 040003. AIP Publishing LLC, 2019.

[5] K. Amellal, C. Tzoganakis, A. Penlidis, and G. L. Rempel. Injection molding of medical plastics: a review. *Advances in Polymer Technology: Journal of the Polymer Processing Institute*, 13(4):315–322, 1994.

[6] Cavity Eye. Molding monitoring and control solutions. `http://cavityeye.com/`, 2019. Accessed: 2022-02-21.

[7] R. Chen, H. Lee, and C. Yu. Application of taguchi's method on the optimal process design of an injection molded pc/pbt automobile bumper. *Composite Structures*, 39(3-4):209–214, 1997.

[8] L. Cibulski, J. Schmidt, and W. Aigner. Reflections on visualization research projects in the manufacturing industry. *IEEE Computer Graphics and Applications*, 42(2):21–32, 2022.

[9] A. Dasgupta, D. L. Arendt, L. R. Franklin, P. C. Wong, and K. A. Cook. Human factors in streaming data analysis: Challenges and opportunities for information visualization. In *Computer graphics forum*, volume 37, pages 254–272. Wiley Online Library, 2018.

[10] R. Ellson and D. Cox. Visualization of injection molding. *Simulation*, 51(5):184–188, 1988.

[11] S. Fathi and A. Behravesh. Real-time measurement of flow front kinematics using quantitative visualization in injection molding process. *Polymer Engineering & Science*, 48(3):598–605, 2008.

[12] M. Gleicher. Considerations for visualizing comparison. *IEEE transactions on visualization and computer graphics*, 24(1):413–423, 2017.

[13] P. Guerrier, G. Tosello, and J. H. Hattel. Flow visualization and simulation of the filling process during injection molding. *CIRP Journal of Manufacturing Science and Technology*, 16:12–20, 2017.

[14] X. Han and H. Yokoi. Visualization analysis of the filling behavior of melt into microscale v-grooves during the filling stage of injection molding. *Polymer Engineering & Science*, 46(11):1590–1597, 2006.

[15] Hans-Heinrich Behrens. Null-fehler-produktion als prozessphilosophie. `https://www.kunststoffe.de/a/fachartikel/null-fehler-produktion-als-prozessphilos-259931`, 2014. Accessed: 2022-05-05.

[16] T. Hutterer, B. Praher, G. Berger, and W. Friesenbichler. Determination of the temperature of an industrial rubber compound after dosing. a new ultrasound based method. 2018.

[17] iba. ibaInCycle. `https://www.iba-ag.com/de/ibaincycle`, 2022. Accessed: 2022-02-21.

[18] Kistler. Process monitoring with comoneo. `https://www.kistler.com/en/product/type-5887a/`, 2017. Accessed: 2022-02-21.

[19] M. Musleh, A. Chatzimparmpas, and I. Jusufi. Visual analysis of

blow molding machine multivariate time series data. *Journal of Visualization*, pages 1–14, 2022.

[20] B. Praher and G. Steinbichler. Ultrasound-based measurement of liquid-layer thickness: A novel time-domain approach. *Mechanical Systems and Signal Processing*, 82:166–177, 2017.

[21] B. Praher, K. Straka, and G. Steinbichler. Nicht-invasive schmelzetemperaturmessung mit ultraschall im spritzgießprozess: Am übergang von der forschung zum industriellen einsatz. *Wissenschaftlicher Arbeitskreis der Universitäts-Professoren der Kunststofftechnik*, pages 120–125, 2018.

[22] A. Satyanarayan, D. Moritz, K. Wongsuphasawat, and J. Heer. Vega-lite: A grammar of interactive graphics. *IEEE transactions on visualization and computer graphics*, 23(1):341–350, 2016.

[23] A. Thiriez and T. Gutowski. An environmental analysis of injection molding. In *Proceedings of the 2006 IEEE International Symposium on Electronics and the Environment, 2006.*, pages 195–200. IEEE, 2006.

[24] TIG. Tig authentig – the mes-solution for the plastic industry. https://www.tig-mes.com/en/software/tig-authentig/, 2020. Accessed: 2022-02-21.

[25] H. Yokoi, N. Masuda, and H. Mitsuhata. Visualization analysis of flow front behavior during filling process of injection mold cavity by two-axis tracking system. *Journal of materials processing technology*, 130:328–333, 2002.

Author Biography

Christian Steinparz received his BSc in Computer Science and his MSc in Artificial Intelligence at Johannes Kepler University Linz, Austria. He is now working at the Visual Data Science Lab at JKU pursuing his PhD. His scientific areas of interest include machine learning, explainable AI, dimensionality reduction, and data visualization.

Thomas Mitterlehner received his PhD in technical sciences from the Johannes Kepler University in Linz (2020). There he did research on additively manufactured injection mold inserts, conformal cooling channels and rapid/additive tooling, and taught in the field of plastics processing. In June 2021, he and three colleagues founded the company Moldsonics, which focuses on ultrasound-based sensor technology in plastics processing.

Bernhard Praher received his Dipl.-Ing. (equiv. to engineering MSc) in mechatronics in 2006. In 2010 he received his PhD working in mechatronics with a focus on laser spectroscopy. Between 2010 and 2021 he worked in a postdoc position at JKU in the field of ultrasound-based process measuring in polymer processing. Together with his colleagues he founded the company Moldsonics in 2021.

Klaus Straka studied mechatronics at JKU after which he worked for various companies in the industry focussing on control systems. Since 2010 he has been working at JKU where he wrote his dissertation on mixing operations in single screw plasticizing units. Since 2015 he is the deputy head of the institute of injection molding technology and an essential contributor to the development of the Linz Institute of Technology (LIT) Factory.

Holger Stitz is a lead researcher at datavisyn. He received his PhD from Johannes Kepler University Linz. His main research interest include biomedical data visualization, provenance, and sensemaking. For more information see http://holgerstitz.de.

Marc Streit is a Full Professor at the Johannes Kepler University Linz in Austria where he leads the JKU Visual Data Science Lab (https://jku-vds-lab.at/). He finished his PhD at the Graz University of Technology in 2011. His scientific areas of interest include visualization, visual analytics, and explainable AI. He won multiple best paper and honorable mention awards at major conferences in the field. Marc is also cofounder and CEO of datavisyn, a spin-off company that develops data visualization solutions for pharmaceutical and biomedical R&D. For more information see http://marc-streit.com.