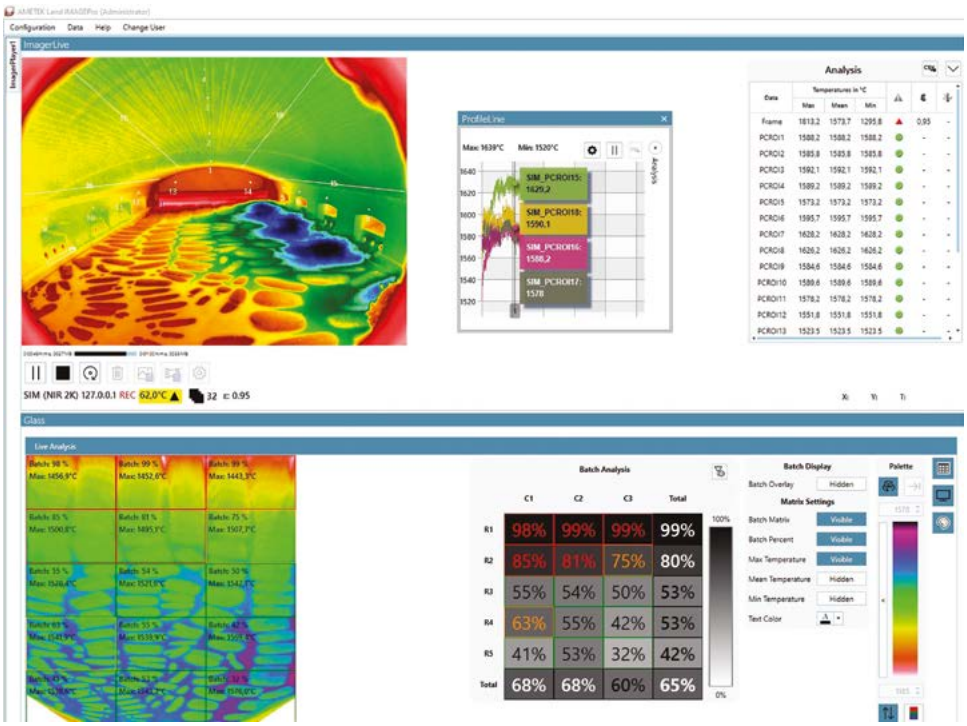
Batch tracking with machine learning and deep neural networks

In glass furnace operations, determining and observing the batch pattern in the melter is essential to achieve stable production. Matt Gillott explains how AMETEK Land is focusing on better monitoring for batch tracking by implementing image processing with neural networks.

To provide a glass product of uniform quality, it is vital to ensure a consistent melt of the batch. This requires monitoring of the furnace to prevent issues such as batch entering the refining zone. However, getting a good picture of the processes inside the furnace can be difficult – flames can obscure the view, cameras can overheat, and making sense of the image can be a problem for untrained operators. To achieve a clearer image of the inner workings of a glass melt furnace, AMETEK Land is implementing cutting-edge machine learning and deep neural network technology, working alongside its high-resolution infrared borescope cameras.

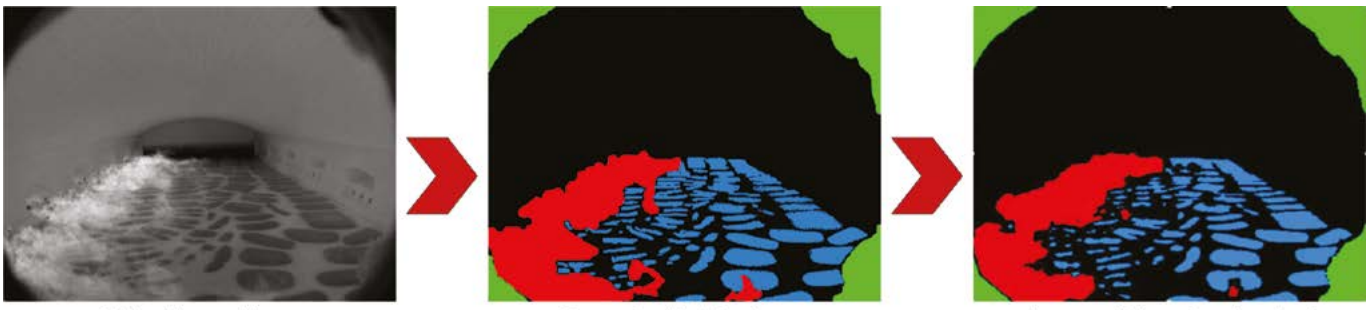
AMETEK Land's IMAGEPro-Glass advanced imaging processing software, combined with high-resolution near infrared borescope thermal imagers for verification and thermal profiling, could easily support operators in adjusting the batch and foaming line identifying the best batch pattern to avoid glass defect and get the proper pull rates. It provides a top 2D view of the melting zone, based on a grid analysis where the critical batch-free location in front of the furnace is monitored. The current model for batch coverage in IMAGEPro-Glass runs well, providing a grid with batch analysis of the melting zone for the users. The next step is to focus on better monitoring for batch tracking, implementing image processing with neuronal networks.



AMETEK Land IMAGEPro-Glass thermal imaging software.

Neural network

Many systems described as artificial intelligence (AI) rely upon a neural network, a highly interconnected and repetitive series of mathematical functions that are trained to perform the required task. The scalability of the neural network has made its use available to a wide range of applications, from recommending which music track you should listen to next and restoring old photographs, to self-driving cars and automatic mass surveillance. The use of neural networks has seen image processing systems become much more capable; for example, the ability to identify an object by pointing your smartphone camera at it demonstrates the capability of an image classification network. The application takes an image as an input and, as the output, generates a probability from a list of known categories. In this case, the system attempts to put the whole image into a single category, but by evolving this approach, it is possible to apply categories to different parts of the image. In the case of furnace monitoring, this allows us to separate out which parts of the image are batch, and which are melted glass. ▸



Example of automatic segmentation of the image.

glass WORLDWIDE

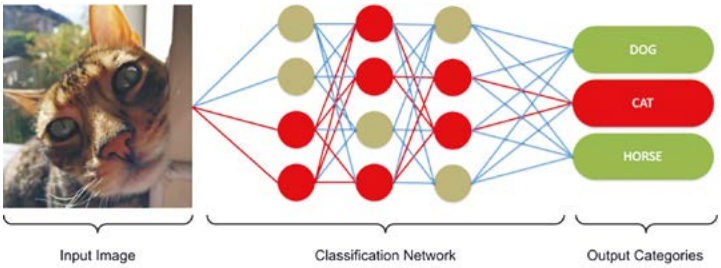
The traditional approach

Traditionally, these image segmentation tasks involved complicated and very carefully crafted algorithms, each of which would be designed for performing a single task. For example, with a glass furnace, one algorithm would need to be written to detect flame, and a separate algorithm to detect batch. In contrast, by using a neural network to perform the segmentation, all the categories can be partitioned in a single pass. Another downside to the traditional approach is that each algorithm also needs meticulous design to handle edge cases and unusual situations – for instance, how to deal with a bright reflection that could cause a false result. As a result, they can be unreliable in some situations or require numerous parameter adjustments to make the algorithm work for a specific task.

Conversely, the performance of a neural network is based upon its architecture and how well it has been trained; adding further training data to the model only improves the performance. During the commissioning of a system, extra data can be collected to ensure optimal performance of the network on the new installation.

Training the neural network

To begin the training process, a set of training data is required. Drawing on its extensive experience in providing solutions for glass applications, AMETEK Land used hundreds of different images from different glass furnaces, cameras, and environments when developing the glass furnace neural network. A glass expert manually segmented each image to differentiate different parts of the image, such as batch, image obscuration, or flame. This formed the primary training data for the network.



Example of image classification neural network.

In addition, several thousand more images were generated from the source images, in a process called data augmentation. This prevents the network from over-learning features that exist in the source images. For example, a common feature when monitoring a furnace through a port is that the corners of the image are obscured, due to the viewing angle and depth of the porthole. When training the network, it mustn't learn that this is a typical feature, as this would lead the network to mark the corners as obscured even when they aren't. Data augmentation prevents this by taking the original images and transforming them with scaling and rotation. This dilutes the number of source images with obscured corners to a smaller proportion.

Once the data has been prepared, the network can be trained by giving it both the input image and the expected segmented result. The training process then attempts to work out how to produce the result from the input. Each image from the thousands of training images is presented to the network multiple times. Every time the network sees an image, some of the parameters adjust, and slowly it starts to understand how to derive features from the input images.

When the training is complete, the network can be tested with images it has not seen before. At AMETEK Land, we used a video recording from the inside of a glass furnace that the network had not seen during training. The result was an impressive automatic segmentation of the image into the categories it was trained to find.

Conclusion

Compared to traditional image segmentation, the neural network offers highly effective performance. The main disadvantage of neural networks lies in the processing requirements. Traditional image segmentation algorithms are highly refined, making efficient use of the available processing power. In contrast, neural networks perform billions of calculations, some of which have no impact on the result and are essentially wasted calculations. This is rarely a problem, however, as most modern PCs are powerful enough to perform these operations at an appropriate speed.

Ultimately, the solution will automatically work on any furnace, up to a point. The commissioning process will then adapt the algorithms to the specific furnace and the network trained with information from that furnace alone, delivering best-in-class classification. For the end-user, this means less commissioning time as well as the ability to adapt the model as a direct result of data collected by the operator and sent back for evaluation.

If a furnace set-up occurs where the current model performs sub-optimally, a furnace specific model could be created from data collected by the user on-site, without the need for an AMETEK Land engineer to visit the site.

There remains much work to be done. AI technology is progressing at a rapid pace, with new and improved network architectures and training methods appearing all the time. AMETEK Land will continue to improve its network architecture and training data to ensure IMAGEPro-Glass software provides the best possible batch tracking solution to its customers. ●

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