The GI dataset for glass inspection
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***Abstract* – In the context of the glass industry, visual inspection is a key point in order to deliver high quality products to the final customers. To address this we have developed and improved the *Glassinspector*, a solution based on video cameras for the automated detection of defects and irregularities on planar surface glasses. The most challenging aspect is represented by the correct classification of the anomalies found, based on the analysis of the images acquired, in order to achieve correct results and successfully meet our customers' requirements. Indeed, depending on the type of glass and its final use, these requirements – in terms of anomalies that should (and should not) be considered as defects – may vary significantly. To address this, we have collected a dataset, composed of 660 images recorded from several installations to test different classification techniques. The dataset is made publicly available and can be downloaded from [1].**

***Index Terms* – glass inspection, machine learning, dataset, classification**

I. Introduction

Automated inspection in the field of the glass industry aims at helping the producer to deliver better products and at the same time to increase the production rates. Anyhow, to successfully replace human inspection, technologies should achieve high levels of accuracy by lowering the rates of false positives and false negatives.

Deltamax is constantly working on the development and improvement of solutions able to comply with the continuously increasing industry requirements. In the context of the RISOLVI project, we had the chance to improve our technologies and to collect an exhaustive number of image samples from various installations at our customers' premises. Those samples were used to define algorithms able to correctly detect and classify defects by tailoring a specific solution to each of our customers' needs. The result is the creation of a dataset that is available to anyone interested in the detection and classification of defects on planar glasses.

The large number of installations allowed us to cover multiple sectors of glass production (e.g. automotive, appliance and architectural industry). The dataset is therefore characterized by a large variability in terms of combinations between glass types and imperfections encountered.

The glasses considered show variations in terms of:

- Chemical Composition (soda-lime, borosilicate and glass-ceramic)
- Treatment (laminated, tempered, coated)
- Transparency (bright, ultra bright and dark).
- Thickness: typically ranging from 2.0 mm to 10.0 mm.
- Dimensions ranging from small custom-cut glasses for the appliance sector to the largest jumbo sized glasses (3660mm by 12500mm).
- Edge finishing (e.g. swiped, flat, round).
- Printed/non-printed.

It should be noted that the samples are collected from real on-site applications and hence match real-case scenarios in accordance with the real requirements of the manufacturers. Images therefore may include dirt, powder and other extraneous factors that should be taken into consideration during the analysis. To the best of the authors' knowledge, there are no similar works currently available.

II. Acquisition specifications

The images contained in the dataset were acquired from various installations of the Glassinspector – our automatic visual inspection solution – at our customers' premises. Our data recording methodology is carefully designed in order to grant high levels of detail with stable and comparable results. The architecture reflects the current state-of-the-art in the industry inspection domain.

One of the peculiarities of the system is the capability of acquiring multiple images of the same scene and combine them together to improve both the detection and the classification of the defects. Examples of some of the possible acquisition channels are [2]:

- bright field in backlight: the lamp is placed in front of the cameras, behind the object. In this configuration the defects appear darker then the background.
- dark field: the luminous flux from the lamp is not targeted on the camera. Defects are brighter than the background.
- bright field in reflection: the luminous flux is reflected from the object before reaching the camera. The lamp and the camera are placed at the same angle with respect to the normal to the glass surface, but lie on opposite sides.

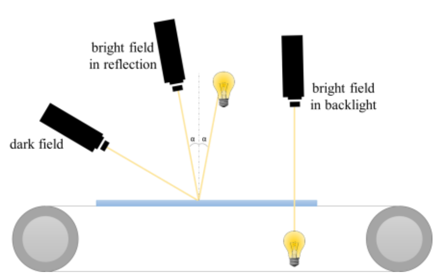

Figure 1. Different acquisition channels setups

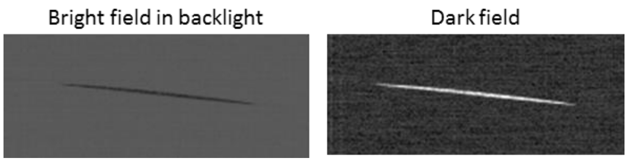

Figure 2. The same defect acquired from different channels

During the research project, we developed a solution able to combine the first two types of inspection together by using only one camera and one lamp. To achieve this behaviour we studied and realized a double light source lamp and an electrical controller that manages the on/off switching of the light. The results obtained are promising in terms of defects detection capability and classification performance with contained production costs. Further details can be found in the following sub-section.

By combining the different channels (i.e. bright and dark field) defects can be extracted more easily: indeed, each class of defect has peculiarities that are more or less noticeable in one specific channel. Therefore, in the dataset, you will find that to each defect is associated one or more images (views), each acquired from one of the different channels used.

A. Setup

The acquisition setup is typically composed of a fixed set of elements. However, variations have to be considered from one installation to the other in order to comply with the specific requirements of each manufacturer and to adapt to each real-case scenario. The most important variation is to be found in resolutions. The resolution is chosen accordingly to the quality level required by the manufacturer, which is strictly related to the final use of the product. The typical range of resolutions is from 0.08 to 0.3 mm/pix[1].

The main components of the acquisition setup are as follows:

- Cameras: we use monochrome line scan cameras of different sensor resolution (2kpix - 8kpix). The specific camera chosen for an installation depends on multiple factors, of which the most significant are the dimensions of the glasses to be analysed, the speed of the line and the physical space available for mounting.
- Optics: similarly as for the cameras, optics are chosen differently for each installation and accordingly to the rest of the setup. The most important factors that influence the choice are the image resolution desired, the working distance and the sensor's dimension and resolution.
- Lamp: as introduced in the previous section, the lamp is in-house produced. Recently, we moved from fluorescent (and halogen) light sources to LED (light Emitting Diodes) technology due to its excellence in terms of: life expectancy, application flexibility, stability, on and off switching speeds and cost effectiveness. The peculiarities of our lamp are:
  - High uniformity in terms of luminosity along its whole length (up to 3500 mm).
  - Great heat dissipation (we achieve constant working conditions by maintaining the LED's temperatures in the range recommended by the producer).
  - Long life expectancy.
  - Contained dimensions in an easy-to-mount configuration.
- Processing unit: it is composed of a PC and a number of in-house produced electrical boards (e.g. image acquisition boards, encoder and lamp control boards).
- Sensors: photocells and encoders are used to synchronize the acquisition with the movement of the glass on the line.

In the following is reported a picture of a typical installation of the Glassinspector at one of our customers' premises.

Figure 3. A typical installation of the Glassinspector

B. Software processing

To meet the diverse needs of our customers with a software solution that was robust but adaptable we decided to create a unique architecture that constitutes the engine of the various control programs. We have developed the Deltamax Vision System (DVS) to be a flexible, programmable and highly configurable framework to realize multi-threaded, multi-process and multi-camera vision based systems for quality control. The principal components of the DVS are the supervisor, the inspectors and the terminals. The supervisor task is to coordinate the work of all inspectors, to fuse the results coming from different sources and to handle all centralized operations such as analog/digital IO, network communication to and from the production line, storage of the results in the DB and the interaction with the terminals. The terminals are local or remote processes devoted to the presentation of the results and the interactions with the operators with a GUI. The inspectors are independent processes dedicated to the analysis of the data coming from a sensor device, each inspector handles a single camera and is in charge of the image acquisition, image pre-processing and analysis, defects detection and classification and it performs all the measurements required for quality control.

The whole inspector's image analysis procedure is programmable using a scripting language, giving to the DVS a

[1] The resolution at which each sample was acquired is a parameter that is reported in the database and it is associated to each defect.

high flexibility and the ability to handle very different tasks within the same framework.

The first steps in the DVS's analysis procedures is the application of image processing techniques with the aim of noise reduction coming from the hardware of the acquisition apparatus. The amount of light that reaches the different cells on the sensor is neither constant in space nor in time. Therefore, thanks to dynamic flat field correction algorithms, the system is able to learn, model and constantly update the behaviour of the light in order to obtain a flat and stable level of light for the background of the image.

Successively, multiple algorithms are applied for defect detection, such as:

- Multipurpose algorithm based on blob analysis
- Line detection using Line Gauss
- Chip detection
- Break detection

The multipurpose algorithm may be broken down into the following steps: region extraction with an adaptive threshold and connected components labelling, filtering of small and low contrast regions, merge of regions using spatial and geometrical features. In the latter step, the algorithm tries to join region that will form specific shapes such as straight and curved lines, marks with small holes or rugged boundaries or low contrasted stains and so on.

The line detection algorithm extracts curvilinear structures and it is based on differential geometric properties of the image function. It is computationally heavier than the blob analysis approach but it permits to extract barely visible scratches with very low signal to noise ratio. This method is based on the work of Steger [3] and has been implemented independently within the DVS library.

The chip detection algorithm analyses the boundary of the glass (or of glass incisions) in order to spot defects caused by glass grinding machine that may break off small pieces of glass. Chips appears in the image with a characteristic shell like shape, inside these shape the chip may appear brighter or darker than the average glass grey tone due to light scattering.

The break detector analyses the glass contour to detect glass breaks and it operates with different strategies based on the specific product. If the glass is grinded, a break will result in a discontinuity in the grinding, in this case the algorithm compares the glass contour with the grinding line. If the shape of the glass is known beforehand, the comparison is made between the model's contour and the sample's contour. Some glass breaks cannot be detected in this way because the external glass boundary is intact, we define such breaks as cracks. The break detector module identifies these cracks extracting dark continuous regions that originates from the external border.

C. Labelling and annotations

The dataset was obtained by manually selecting and validating a set of images previously collected from the Glassinspector. Indeed, the whole process involved two different phases: an autonomous one and a human driven one.

The first phase, performed autonomously by our system, was the one providing the cropped images of the detected defects from each of the multiple acquisition channels. As detailed in the previous section II.B, the DVS is characterized by a configurable image processing procedure that can be simplified as follows:

- Image acquisition: glasses are scanned while transiting on the conveyor belt. For each sample, one or more images (from the different channels) are stored.
- Detection: each image is analysed in parallel by a number of algorithms specifically designed in order to detect discrepancies in the glass. The outcome are regions of interest (ROIs) highlighting areas where defects may be found. Together with ROIs, the detectors provide the position of the non-conformant pixels using the run-length encoding (RLE).
- Classification: an automatic classifier establishes, on the basis of the different ROIs and runlists found, the type of defect encountered.

Figure 4 schematizes this process.

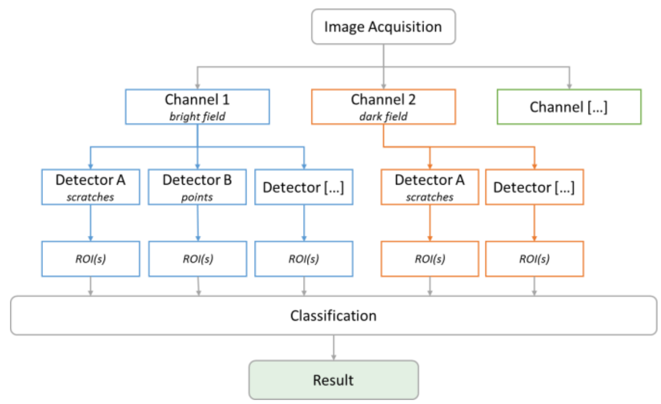

Figure 4. Schema of the autonomous phase

The second phase required human interaction. Each ROI extracted was manually verified in-house by visual inspection. As a requirement, the selection process was carried out in order to have an homogenous distribution and variability in terms of characteristics of the defects found. In the cases where the class of the defect was not clearly addressable from the image, we verified it on the real glass sample. This operation was clearly not possible in all cases given that the glass may have already been destroyed or recycled. These cases were removed from the dataset.

The final result is a collection of defects, described by multiple ROIs acquired from multiple channels, that are labelled in two sets: type and severity.

1) Type

Defines the class associated with the type of defect found. The type of a defect can assume, exclusively, one out of the following classes:

point	Presence of small extraneous materials. Can be typically described as a small, non-elongated, highly contrasted and dense region.
point_set	An area characterized by the presence of multiple and narrow points.
bubble	Air bubbles contained inside or on the surface of the glass structure.

mark	It is an easily visible (highly contrasted) medium to large area found on the glass surface.
stain	Similarly to the mark, it is an area of medium to high size but it is less visible. It typically is dirt (e.g. marks caused by the rollers).
scratch_light	A thin and shallow cut or mark on the glass surface typically caused by a sharp instrument.
scratch_heavy	A thin and shallow cut or mark on the glass surface. More easily visible with respect to the scratch_light.
chip	Small pieces (fragments) of glass missing from the border of the sample.
crack	Identifies a broken glass without complete separation of its parts.
printing_error	When applicable, describes an error occurred during the printing phase. The defect may highlight that some parts of the print are missing or that there is abundance of ink. This is extracted by comparison with a given model.
no_defect	Wrongly detected areas where no defect is present at all.

An overview of all classes available and their distribution in terms of number of examples per class is reported in the following figure.

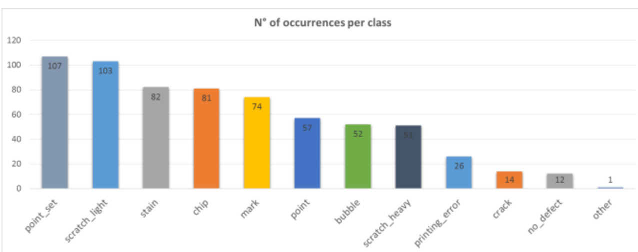

Figure 5. Distribution of the number of classes in the dataset

The total number of defects contained in the dataset is 660, of which the majority is composed of scratches, points, stain and chips. Those classes are in fact the most common to be encountered in the planar glass production. Unfortunately, for some classes – specifically cracks and printing errors – we were not able to collect the same amount of examples as for the rest of the dataset.

The correct classification of the type of defect is challenging, but represents a key aspect: it is a valuable feedback for the quality manager to better understand where the problem resides and possibly find an appropriate solution.

2) Severity

Severity associates to each defect an index representing the magnitude of the problem encountered: the higher the index, the worse the problem. Currently, we have defined three different levels of severity, which can be associated to Green, Yellow and Red.

Green	Contains defects that comply with the restriction imposed by the quality management of the factory.
Yellow	Defects that are borderline and may require validation from a human inspection.
Red	Defects that exceed the quality restrictions and cause the piece to be rejected.

By mistakenly associating the severity level, we may reject a sample that was instead compliant with the manufacturer's quality restrictions or vice-versa accept glasses with out-of-bound defects. The correct classification of this parameter is of special importance in the case of non-supervised systems. Being these strictly related to each manufacturer's needs, the classes are provided as-is, for the reader to appreciate the average sensitivity required by our customers.

The most challenging aspect in the definition of a classifier for the severity is the need of having some changeable parameters during production: the operator should be able to modify the classifier in order to meet the specific requirements of a particular type of glass or of a specific customer. Therefore, we should provide a set of easily understandable parameters (e.g. area, length, contrast) that can be changed in real time and do not require re-training the classifier in order to achieve the results desired.

III. Structure of the Dataset

The dataset is provided in the form of a database (we used MySQL Server 5.6.16 and WorkBench6.0 CE specifically[2]) and contains 660 accurately labelled defects composed of 1160 views.

An overall schema of the database reporting the tables, fields and their interactions is reported in Figure 6.

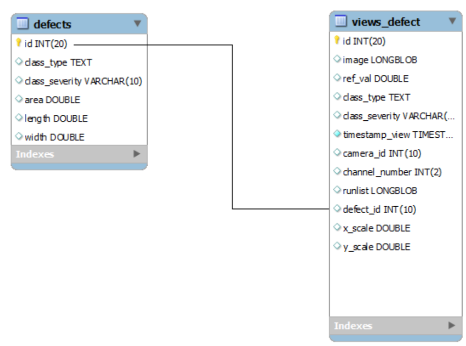

Figure 6. Overall schema of the database

A. Table "Defects"

It is the leading table of the dataset where each record represents a different defect. Records are composed of a number of fields used to characterize the defect found. The following table reports the meaning associated to each field.

Field	*Type*	*Description*
id	int	Unique identifier of the defect.
class_type	text	The class associated to the defect.
class_severity	int	The severity level associated to the defect. Range [0 - 3].
area	double	Area covered, expressed in mm^2.

[2] To correctly import the dataset, once downloaded, load it using "Import from Self-Contained File".

length	double	Dimension of the defect on the y direction. Expressed in mm.
width	double	Dimension of the defect on the x direction. Expressed in mm.

B. Table "View_defect"

This table contains the ROIs (views) extracted from the various acquisition channels. Each view is associated to a defect.

Field	*Type*	*Description*
id	int	Unique identifier of the defect.
img_png	long blob	Image of the defect, in Portable Network Graphics format (.png).
ref_val	double	Average value of the gray tone level of the whole glass sample.
class_type	text	The class associated to the defect.
class_severity	integer	The severity level associated to the defect. Range [0 - 3].
timestamp_view	datetime	Date and time of the acquisition.
camera_id	int	Identifier of the camera that acquired the image.
channel_number	int	Identifier of the channel the image belongs to. [0=bright field in reflection, 1= bright field in backlight, 2=dark field]
runlist	long blob	Mask of the pixels detected as non-conformant.
defect_id	int	Reference to the defect to which this view is associated in the "Defects" table.
x_scale	double	Resolution in the x dimension, expressed in [mm/pix].
y_scale	double	Resolution in the y dimension, expressed in [mm/pix].

IV. CONCLUSIONS AND FUTURE DEVELOPMENTS

In this paper we have presented a dataset of defects commonly found in the planar glass production industry. The dataset is intended to be freely usable and publicly available.

This dataset is particularly valuable from the authors' point of view since it provides an exhaustive number of samples collected from real on-field scenarios. Indeed, we want to stress out the importance of such acquisitions when compared with those collected from a controlled environment (i.e. in-lab tests) that cannot – given their nature – consider a large variety of external factors. Additionally, being quality inspection on planar surfaces not a novel application, we were surprised not to find similar works already available in literature.

In future releases, we plan to increment the number of samples, not only by adding new images, but also by testing new acquisition methodologies (e.g. changing light conditions, cameras setups and moving from the visible spectrum to other spectral lengths).

Lastly, we look forward for possible collaborations to test novel approaches specifically in the field of glass inspection but also, more generally, in the field of surface defects detection.

FUNDINGS

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