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A PROTOTYPE LOW-COST MACHINE VISION SYSTEM FOR AUTOMATIC IDENTIFICATION AND QUANTIFICATION OF POTATO DEFECTS.J Hutton¹, G Harper² and T Duckett¹¹*University of Lincoln, School of Computer Science, Brayford Pool, Lincoln LN5 7TS*²*AHDB Potato Council, Sutton Bridge Crop Storage Research, Spalding PE12 9YD**E-mail: jhutton@lincoln.ac.uk, glyn.harper@potato.ahdb.org.uk, tduckett@lincoln.ac.uk*

Summary: This paper reports on a current project to develop a prototype system for the automatic identification and quantification of potato defects based on machine vision. The system developed uses off-the-shelf hardware, including a low-cost vision sensor and a standard desktop computer with a graphics processing unit (GPU), together with software algorithms to enable detection, identification and quantification of common defects affecting potatoes at near-real-time frame rates. The system uses state-of-the-art image processing and machine learning techniques to automatically learn the appearance of different defect types. It also incorporates an intuitive graphical user interface (GUI) to enable easy set-up of the system by quality control (QC) staff working in the industry.

INTRODUCTION

The British potato industry delivers sales-value of £743m at the farm gate and £3.5bn at consumer level, and potatoes account for 40% of the carbohydrate consumed in the UK. For the fresh market, the main factor affecting consumer preference is physical appearance with clear unblemished skin a significant selling point. Potatoes with defects, diseases and blemishes caused by otherwise benign (to human) skin infections, are strongly avoided. Most potatoes are sorted into different grades by hand, with inevitable mistakes and losses.

This paper reports on the current progress of a project to develop a prototype low-cost machine vision system for the automatic detection, identification and quantification of common defects at near real-time frame rates. The prototype is designed to enable accurate monitoring of individual potatoes as well as aggregation of summary statistics for a sample of potatoes. For example, the summary report lists the proportion of potatoes in a sample affected by different defects, such as common scab, black dot, silver scurf, greening, etc. While the primary intended application of the prototype system is in quality control, the technology also has potential for online application in potato processing and packaging facilities to enable accurate monitoring of an entire harvest of potatoes.

MATERIALS AND METHODS

Hardware Setup

The prototype system uses off the-shelf hardware, including a low-cost machine vision sensor and a standard desktop computer. To enable real-time performance the computer is also equipped with a graphics processing unit (GPU), namely an NVidia GTX 750, which uses parallel processing to accelerate some of the required image processing functions.



Figure 1. Image acquisition - A tray containing potatoes is placed inside the light box, then the box is closed by placing the door on the front (not shown in the picture), attached with magnetic fixings, and an image is captured from the overhead camera for analysis by the system.

Consistent lighting is important for the accuracy and consistency of the system. Therefore, a custom made light-box was built to hold a standard sized tray for quality control purposes (Fig. 1). The floor of this tray measures around 300mm x 400mm, and the tray is capable of holding approximately 12 potatoes, depending on their size. Four battery-powered LED lights were mounted on the ceiling of the light box. Each light was covered with a diffusing plastic material, to ensure reasonably even lighting levels across the tray and to reduce the influence of shadows from the potatoes in the captured images.

The hardware used for image capture is a Logitech C910 HD web-camera capable of taking images with a resolution of 10 megapixels, mounted in a central position in the ceiling of the light box.

Graphical User Interface

A graphical user interface (GUI) was developed to allow the software to be used by quality control experts from the industry (Fig. 2). Within a few button presses the system can be trained to recognise different defect types and then used to analyse potatoes in real-time. An important aspect in the design of the GUI concerns how to achieve an efficient and accurate way for the user to mark-up defective and non-defective areas of a few selected potatoes. This

is important because the system relies on the human expert to provide examples of areas of unblemished potatoes as well as the different defect types, from which the machine learning algorithms used by the system are able to learn the appearance models required to discriminate between the different defect types.



Figure 2. The current prototype interface.

An overview of the GUI is provided in Figure 2, where the two smaller images on the left hand side represent the webcam feed (top) and a visual representation of the user-selected data on which the machine learning classifier has been trained (bottom). The final larger window is used initially for the user mark-up of selected potatoes for training the system, and then for displaying the classifier output when the trained system is used for quality analysis. Finally, the GUI displays a summary report giving the percentage of the classified area for unblemished potato as well as for each defect type (see Fig. 5 for an example).

An image is captured by pressing the “capture image” button and then pressing the “remove background” button to extract the potatoes, setting the background pixels to a neutral colour. There is also a corresponding “learn background” button to learn the appearance of the image background after first taking an image of the empty tray. The tray does not need to be in exactly the same position between images. The user mark-up is carried out by first selecting a user-defined class or category (e.g. “non-defect”, “defect type 1”, “defect type 2”, etc., where the defect types could correspond to common scab, silver scurf, black dot, etc.) and selecting pixel areas within the image that correspond to that particular class to provide training data. The user presses the “train classifier” button when the mark-up is finished. The user can then press the “classify” button to analyse entire images of potatoes in the tray, producing an output image where every part of the potatoes has been colour-coded according to the categories assigned by the trained classifier. The high computational speed of the system, producing

almost instant results, means that the user can interactively refine the trained classifier by adding or removing additional areas of the potato to include in the training data for each class (e.g. parts of the potatoes which were initially misclassified due to insufficient training data).

Once the user is satisfied with the set-up and training of the system, the trained classifier can be used to classify as many trays of potatoes as desired, provided that the potatoes are sufficiently similar to those used to train the system. The system can be quickly retrained to work with different potato varieties, diseases and lighting conditions, etc.

Automatic Defect Identification

The software for image processing and machine learning used for defect detection and identification is based on the earlier work by Barnes *et al.* (2010a, 2010b). In this approach, classifiers are trained to detect and identify defects using colour and texture features extracted from the image. A very large set of candidate features, based on statistical information relating to the colour and texture of the region surrounding a given pixel, is first extracted. A machine learning algorithm (known as AdaBoost) is then used to automatically select the best features for discriminating between defects and non-defects, and also to discriminate between the different types of defects. With this approach, different image features can be selected for different potato varieties, while also handling the natural variation in fresh produce due to different seasons, different lighting conditions, etc.

While the above-mentioned research established the “proof of concept” for this project, the previous work did not include development of any interface for training the system, nor did it include processing of the images in real-time (the previous software developed would take several hours to analyse a single image). Therefore, some of the important developments in this project to realise the prototype system included developing the graphical user interface (as described above) and also the re-implementation of the system using heterogeneous computing. Heterogeneous computing systems use a variety of different types of computational units, including here a general-purpose processor (GPP) with four processor cores and a graphics processing unit (GPU) for accelerating many of the more computationally expensive image processing functions. Consequently the prototype system is currently capable of running at 30 frames per second using the live feed from the web-camera. This means that the system still has spare computational power for further improvements and development of the technology.

RESULTS

The screen capture shown in Figure 3 demonstrates how a human expert would mark-up images by simply selecting areas of particular defects. This data is then passed onto the machine learning algorithm to determine the features that best separate the different classes. The screen capture shown in Figure 4 shows the corresponding output of the trained classifier when used to analyse the whole image of potatoes. Figure 5 shows the corresponding summary report, taken from the graphical user interface, showing the percentage of the classified area for unblemished potato as well as for each defect type.

Once trained, the system can be used to classify potatoes with very similar general features and can be very simply retrained to improve particular class recognition.

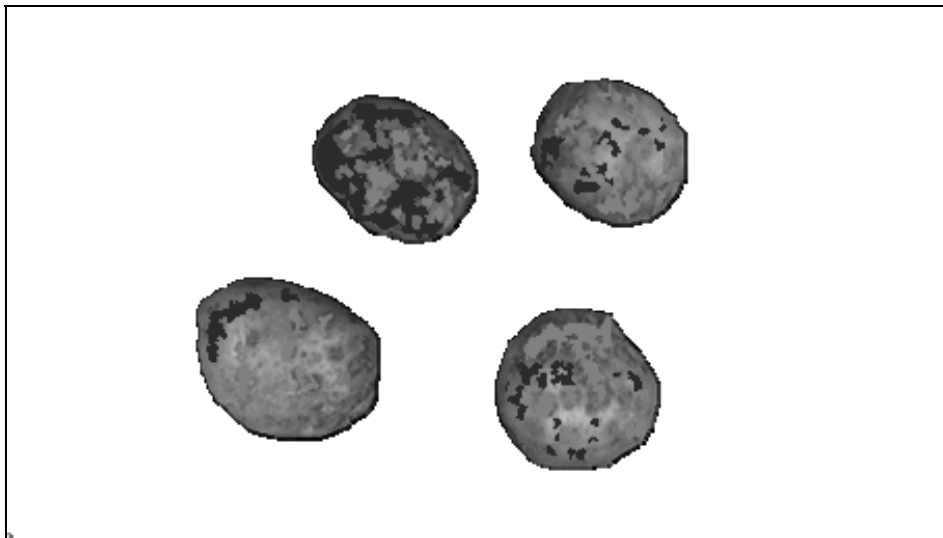


Figure 3. Mark-up of a set of potatoes with common scab (marked in light grey) and unblemished skin (marked in dark grey)

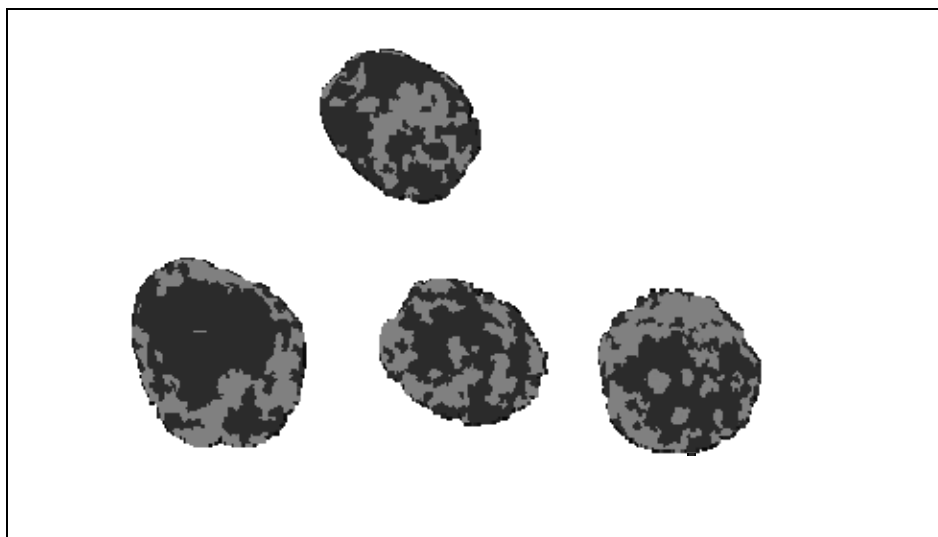


Figure 4. A classified image of potatoes using the classifier trained from the data in Figure 3.

CONCLUSION

In conclusion, a prototype system for automatic defect detection has been developed. A number of planned improvements will enable the system to be more robust with respect to different potato samples and image capture environment. Another extension would be to add a database of previously trained classifiers for different types of potatoes and potato defects, which could then be recalled and re-used as needed, without having to retrain the system from scratch each time.

Overall the system has many benefits to QC staff, improving consistency, speed and accuracy of defect identification and quantification. However, the system is not a replacement for the human element of quality control, as this research aims to produce an aid to experts but not a replacement. Therefore, if the training completed by the human expert is inaccurate and inconsistent, then the system itself will classify and calculate the defective areas incorrectly due to the poor quality training.







Classified Data			
	Class	Amount Classified	Percentage
Unblemished		928	66.6%
Common Scab		465	33.4%
Silver Scurf		0	0.0%
Black Dot		0	0.0%
Greening		0	0.0%
		0	0.0%

Figure 5. Summary report showing the percentage of the classified area for unblemished potato as well as for each defect type, using the same example shown in Figures 3 and 4.

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