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Visual Bean Inspection Using a Neural Network

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***Abstract* - This paper describes a neural network based machine vision system designed for inspecting yellow beans in real time. The system consists of a camera, lights, a belt conveyor, air ejectors, and a computer. Beans are conveyed in four lines on a belt and their images are taken by a monochrome line scan camera when they fall down from the belt. Beans are separated easily from their background on images by back-lighting. After analyzing the image, a decision is made by a multilayer artificial neural network (ANN) trained by the error back-propagation (EBP) algorithm. We use the global mean, variance and local change of gray levels of a bean for the input nodes of the network. In an our experiment, the system designed could process about 520kg/hour.**

I. INTRODUCTION

In market, nowadays, consumers often select agricultural goods by the quality. Since their quality can not be kept uniformly unlike manufactured goods, producers or merchandizers inspect them piece by piece before shipping when they want higher price. Often the most important criterion for the quality inspection is the appearance of a product such as size, shape, and color, which can be checked by vision. In past visual inspection was usually done by human eyes but the rapid increase of labor cost and the production volume of agricultural goods made automatic methods using machine vision techniques popular. Apples[1-4], carrots[5] and potatoes[6], for example, were inspected by analyzing their images using area cameras while rices[7] were inspected using arrays of photo-sensors. Beans, which this paper deals with, however, are too small to be analyzed thoroughly for each piece unlike fruits and too large to be checked simply by photo-sensors unlike rices.

The system designed in this paper uses a high speed monochrome line scan camera to inspect moving beans so that a large volume of beans can be processed in real time. The gray level distribution of pixels of a bean's image is compared with those of good and bad samples. If a bean is regarded as a bad one, it is ejected by activating a high pressure air gun. Since the criteria of the decision making vary by operator (or producer or merchandizer), an ANN is employed to learn the user's different criteria. Global and local characteristics of a bean's image are used for the input of a 2-layer ANN trained by EBP algorithm.

II. THE SYSTEM STRUCTURE

The system built can be divided largely into 3 parts for conveying, inspecting, and computing. The conveying part consists of a bean feeder, air stabilizer, a belt, and air guns. The feeder supplies beans to the belt evenly by vibration. Beans falling down to the fast-moving belt are stabilized preventing from being bounced back by air flow generated in the speed of the belt motion. The belt is driven by a servo motor and a constant speed is maintained using an encoder. Beans are moved in lines by 4 channels made on the belt. Lining up beans makes the design of other parts such as vision and ejection easy. Immediately after beans fly down from the end of the belt, their images are taken and inspected by a line scan camera using back-light. If a bean is determined as a bad one, an air gun in front of the fall trajectory of the bean shoots it. Four digital signal processors (DSPs) on a image processing board and a PC are used for real time computing. Figure 1 shows the structure of the system built.

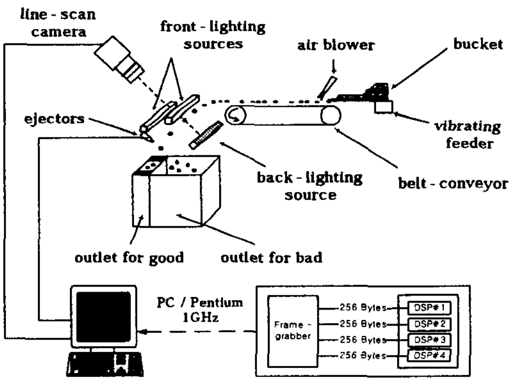


Figure 1. The schematic diagram of the bean inspection system.

III. Neural Visual Inspection

After checking yellow beans manually, we found that they could be grouped in 3 bad bean classes (BBCs) and a good bean class (GBC) as shown in table 1. Beans of BBC2 are relatively simple to be identified while beans of BBC1 and BBC3 are not. Especially, beans belong to BBC1 are hard to be identified from the gray level histogram. So, we defined and used Valley Depth(VD), which is shown in figure 2, for a line scanned.

Table 1. Classification of beans. (GBC: Good Bean Class, BBC1-3: Bad Bean Classes 1-3)

Example of beans	Bean classes		Names
	Good		GBC
	Bad	Surface is not smooth	BBC1
		Brightness is too dark in whole	BBC2
		Brightness is too dark in some part	BBC3

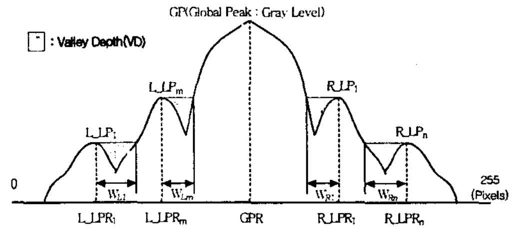


Figure 2. Definition of VD (valley depth) from the pixel gray levels of a scanned image line.

The VD for image line can be defined by

$$VD = \sum_{i=1}^{m} \sum_{j=L\_LPR_i}^{L\_LPR_i + W_{Li}} (L\_LP_i - P_j) + \sum_{i=1}^{n} \sum_{j=R\_LPR_i - W_{Ri}}^{R\_LPR_i} (R\_LP_i - P_j) \quad (1)$$

where m and n are the numbers of valleys in the left and right side of the GP(Global Peak) respectively while w_i is the width of the i'th valley. If the image of a bean has k scanning lines, VD can be summed and normalized by

$$VS = \left(\sum_{i=1}^{k} VD_i \right) \Big/ \#(\text{Pixels\_of\_a\_bean}) \quad (2)$$

Since there is no explicit standard of goodness or badness for beans, decision making is ambiguous. Actually "how much dark" or "how much smooth surface" to judge a bean as one belong to a class among the four defined in table 1 is different by person who uses the machine. So, we let the decision be made by an ANN trained by sample beans classified manually by a machine user. A 2-layer feedforward network shown in figure 3 was used for the purpose. The input values are the mean and variance of gray levels in addition to VS defined in eq.(2). The EBP learning algorithm with sigmoidal activation functions is used.

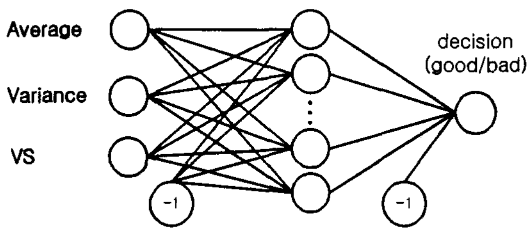
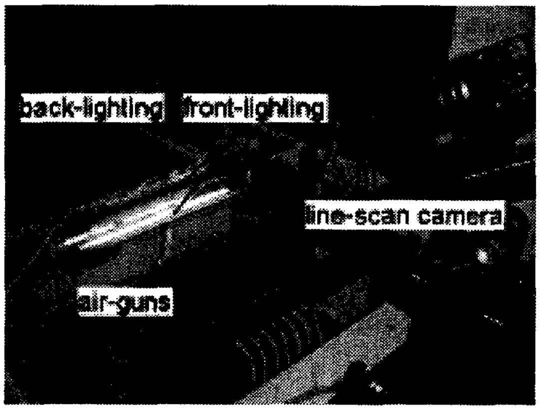


Figure 3. ANN for inspecting beans.

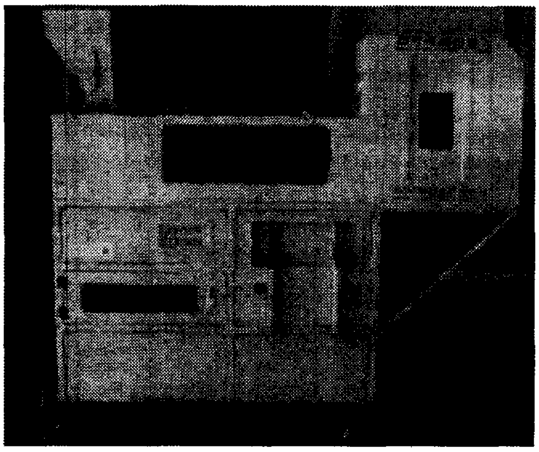
IV. RESULTS

The bean inspection system designed in this paper employs a monochrome line scan camera from Basler. A line scanned for a bean has 256 pixels because the camera consists of 1024 pixels and beans are moved in 4 lines. The frame grabber and image processing board with four DSPs (TMS320C6201@200MHz) from Coreco are used. A Pentium-III(1GHz) industrial PC is used and the algorithm proposed is programmed in C++. Figure 4 shows the inspection system we finally built and went to the market by Daewon G.S.I. Co., Ltd.

For experiment, 90 beans of 3 bad classes and 30 good beans were selected manually. The beans were then fed to the system and an ANN in the structure of figure 3 was trained. After training, the network was used for inspecting other 120 beans, where 30 were good again. Table 2 shows the results. The success rate was about 94% and the machine could process beans of 520kg/hour approximately.



(a)



(b)

Figure 4. The inspection machine built : (a)vision part, (b) outlook.

Table 2. Result of test inspection. In total 120 good and bad beans manually selected were inspected after training an ANN with different but the same number of beans.

	Results		Correct
Decision	Good	Bad	Decision Rate(%)
GBC	28	2	93.3
BBC 1, 2, 3	4	86	95.5

V. CONCLUSION

An automatic beans inspection system was built based on machine vision techniques. Real time processing was an important factor in the system design and we employed a monochrome line scan camera, a high speed frame grabber and an image processing board with multiple DSPs. Beans moved by a belt conveyor were scanned and their images were analyzed. If a bean was regarded as a bad one, it was ejected by an air gun. Otherwise it was collected in a bin.

Since the decision criteria are ambiguous unlike the cases of inspecting manufactured goods, explicit thresholds could not be set and used. Instead an ANN was trained using samples selected manually by a human user before running the machine. A common EBP algorithm was used to train a 2-layer feedforward network.

In an experiment, the system built could inspect beans over 500kg per hour. The decision success rate was about 94%.

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