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Automated Visual Inspection to Detect Cracks in Bottles Using Neural Network

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Abstract

Advances in computer technology have produced a surge of interest in image analysis during the last decade. Considerable efforts have been dedicated to solving the problem of recognition and characterization of object found in an image. Until the 70's the use of optical techniques was predominant. Since the beginning of the 80's due to the advances in the microelectronics field and the developments of parallel architecture, digital techniques have been applied. The issue of quality control is an important aspect of today's highly competitive industry. One important way to improve the quality of the end product is to inspect the output of each manufacturing process. However, manual inspection of end product slows down the entire process as it becomes costly, time consuming and also may impact the effectiveness of human labour due to the hazardous atmosphere of industry. Data set for minor and major cracks obtained were used to train neural network classifiers using a Back propagation algorithm. A performance goal of 95% is reached after training. A Back propagation algorithm is a reliable classifier in machine vision.

Keywords: **R**ecognition, **M**icroelectronics, **B**ack propagation, **N**eural network, **C**lassifier

Introduction

Traditionally visual inspect and quality control are by human experts. Although human can do better than machine in many cases, they are slower than the machines and get tired quickly. Moreover, human experts are difficult to find or maintain in an industry, require training and their skill may take time to time develop.

Computer vision may effectively replace human inspection in such demanding cases. In a typical industry vision system, first a computer is employed for processing the acquire images. This is achieved by applying special purpose image processing analysis and classification software. Images are usually acquired by one or more cameras placed at the scene under inspection. The positions of the cameras are usually fixed. In most cases industrial automation systems are designed to inspect only known objects at fixed positions.

There exists an industrial vision capable of handling all tasks in every application field. Only once the requirements of a particular application domain are specified, then appropriate decisions for the design and development of the application can be taken. The 1'st problem to solve in automating a machine vision tasks is to understand what kind of information the machine vision system is to retrieve and how this translated to specify in measurements or features extracted from images.

The requirements for the design and development of successful machine vision system vary depending on the application domain and related to the tasks to be accomplished, environment, speed e.t.c

For example, in machine vision inspection application; the systems must be able to differentiate between acceptable and unacceptable variation or defects in products.

Finally, an industrial vision system must be fast and cost efficient. In this we emphasize the attributes of an industrial machine vision inspection system such as flexibility, efficiency in performance, speed and cost, reliability and robustness. In order to design a system that maintains those attributes it is important to clearly define its required information from raw images according to the following sequence of steps.

1. **Image Acquisition**: Images containing the required information are acquired in digital from rough noise cameras, digitizer e.t.c
2. **Image Processing:** Once images have been acquired, they are filtered to remove background noise or unwanted reflections from the illumination system. Image restoration may also be applied to acquisition system e.g. cameras.
3. **Feature Extraction**: A set of known features characteristic for application domain, is computed, probably with some consideration of non-overlapping or uncorrelated features so that classification can be achieved. Examples of such features include size, position, contour measurement via edge detection and linking as well as the texture measurement regions. Such features can be computed and analysed by statistical or other computing techniques (e.g. neural networks or fuzzy system)
4. **Decision-Making:** The 1st step in decision making attempts to reduce the dimensionality of the features space to the intrinsic dimensionality of the problem. The reduced feature set is processed further as to reach a decision. The decision as well as the types of features and measurements (the image description) computed, depends on the application.

INTRODUCTION TO NEURAL NETWORKS

Neural Network simultaneous appears to be a recent development. However, this field was established before the advert of computers, and has survived at least one major setback in several areas. The 1st artificial neutron was produced in 1943 by the neurophysiologist Warren Culloch and the logical Walter pits.

An Artificial Neural Network (ANN) is an information-processing paradigm that is inspired by the way of biological nervous system, such as the brain; process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANN like people learns by example. It is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connection that exist between the neurons.

Neural Networks Versus Conventional Computers

Neural Networks take a different approach to problem solving than that of conventional computers. Conventional computers used an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known, the computer cannot solve the problems that we already understand and known how to solve. But the computers would be so much useful if they could do things that we don't exactly know how to do.

Neural Network process information in a similar way the human brain does. The network is composed of large number of highly interconnected processing elements (neurons) networking in parallel to solve a specific problem. Neutral networks learn by example. They cannot be programmed to perform a specific task.

The example must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable.

Neural networks and conventional algorithmic computers are not in competition but complement each other. Their tasks are more suited to an algorithmic approach like arithmetic operations and task that are more suited to neural networks. Even more, a large number of tasks require systems that used a combination of the two approaches (normally a conventional computer is used to supervise the neural network) in order to perform at maximum efficiency.

Simple Neuron

An Artificial Neuron is a device with many inputs and one output. The neuron has two nodes of operation; the training modes and the using mode. In the training mode, the neuron can be trained to fire (or not), for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. If the input pattern does not belong in the taught list of input patterns, the firing rule is used to determine whether to fire or not.

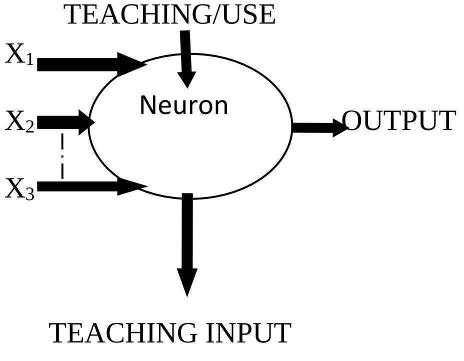

FIGURE 1: A Simple Neuron

Feedback Networks

Feedback networks can have signals travelling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until input changes and a new equilibrium need to be found. Feedback architectures are also referred to as interactive or recurrent, although the latter term is often used to denote feedback connections in single player organizations.

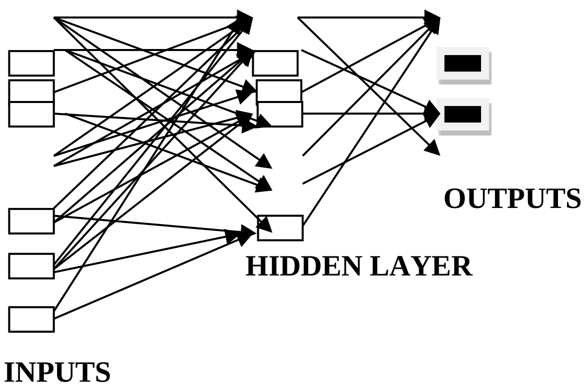

FIGURE 2: An example of a Simple Feed Forward Network

METHODOLOGY

Design Consideration &Analysis

Below shows the functional block diagram of the various procedural steps to be taken during the course of the research project.

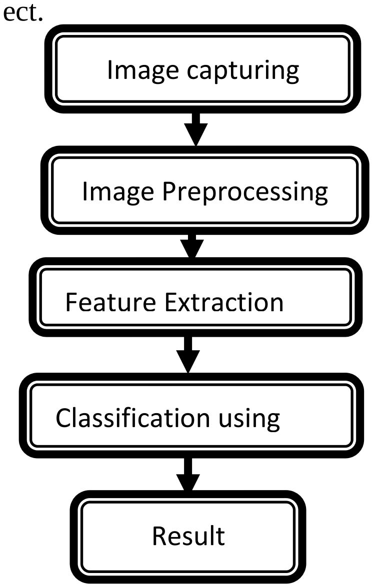

FIGURE 3: Sequence of Experimental Procedure

A. Image Capturing

The raw image of the glass bottle is captured with the use of camera, which is interfaced to the memory of a computer-processing unit.

A camera is a device that converts a pattern of radiated energy into a digital image stored in a random access memory. The typical visible light monochrome camera could have a radiation of 640x480 pixels, produce 30 frames per second and support electronics shuttering and rapid reset. It would be based on the CCD technology that produces good image quality.

B. Image Preprocessing

Certain algorithms and processes are applied on the acquired digital image for preprocessing. The algorithms also known as image enhancement algorithms include point transforms and neighborhood operation.

Point transforms produce output images where each pixel is some function of a corresponding input pixel. The function is the same for every pixel, and is often derived from global statistics of the image. With neighborhood operations, each output pixel is a function of a set of corresponding input pixels. This set is called a neighborhood because it is usually some region surrounding a corresponding center pixel, for example a 3x3 neighborhood. Point transforms generally execute rapidly but are limited to global transformations such as adjusting overall image contrast.

Neighborhood operations can implement frequency and shape filtering other sophisticated enhancements, but execute more slowly because the neighborhood must be recomputed for each output pixel.

i. Illumination

All image-processing application starts with some form of illumination typically light but more generally some form of energy. In some cases ambient light must be used but more typically, the illumination can be designed for application. The simplest illumination setup for image acquisition systems consists of a single point source to give light over the field of view of a camera. Encountered problems are different, but some of the most significant are shadows and non-uniforms illumination of different parts of the inspected objects. Non uniform illumination can make image segment.

ii. Histogram Specification

Is a powerful pixel mapping point transform wherein an input image is processed so that it has the same distribution of pixel values as some reference image. The pixel map for histogram specification is easily computed from histograms of the input and reference images. Histogram specification is a useful enhancement prior to an analysis step whose goal is some sort of comparison between the input and the reference.

iii. Thresholding

Is a commonly used enhancement whose goal is to segment an image into object and background. A threshold value is computed above (or below) which pixels are considered "object" and below (or above) which "background". Sometimes two thresholds are used to specify a band of values that correspond to object pixels. The thresholds can be fixed but are best computed from image statistics.

Thresholding can also be done using neighborhood operations. In all cases the result is a binary image-only black and white are represented, with no shades of gray.

iv. Colour Space Conversion

Is used to convert between, for example, the RGB space provided by a camera to the HIS space needed by an image analysis algorithm. Accurate colour space conversion is computationally expensive, and often crude approximations are used in time critical applications. These can be quite effective, but it is a good idea to understand the tradeoffs between speed and accuracy before choosing an algorithm.

v. Time Averaging

Is the most effective method of handling very low contrasts images. Pixel maps to increase image gain are of limited utility because they affect signal and noise equally. Neighborhood operations can reduce noise but at the cost of some loss in image fidelity. The only way to reduce noise without affecting the signal is to average multiples images over time. The amplitude of uncorrelated noise is attenuated by the square root of the number of images averaged.

vi. Linear Filters

Are the best understood of the neighborhoods operations, due to the extensively developed mathematical framework of signal theory dating backs 200 years to Fourier. Linear filters amplify or attenuate selected spatial frequencies, can achieve such effects as smoothing and sharpening, and usually form the basis of re-sampling and boundary detection algorithms. Linear filters can be defined by a convolution operation, where output pixels are obtained by multiplying each neighborhood pixel by a corresponding element of a like shaped set of values called a kernel, and then summing those products.

vii. Immediate Application to Filters (Boundary Detection)

Edge detection process assumes the glass bottle is smooth enough. The bottle surface image is filtered for the removal of noises added up due to the acquisition process. The shading produced by the bottle in the image is among the least reliable of the bottle properties, since shading is a complex combination of illuminations, surface properties, projection geometry, and sensor characteristics. Image discontinuities, on the other hand, usually corresponding directly to object surface discontinuities (e.g. edges), since the other factors tend not to be discontinuous. Image discontinuities are generally consistent geometrically (i.e. in shape) even when not consistent photometrically. Thus identifying and localizing discontinuities, which is the goal of boundary detection, is one of the most important digital image processing tasks. Boundaries are usually defined to occur at points where the rate of change of image brightness is a local maximum, i.e. at peaks of the first derivative or, equivalently, zero crossings of the second derivative.

C. Features Extraction

The goal of this research is to detect surface cracks in bottles using neural networks. A defect in a material is characterized by the texture of the material. A texture is defined as the character of a surface as determined by the arrangement of size, particles or constituents parts. The defects could be characterized as shown in table 1. The characteristics features of the bottled image are extracted. The defect is characterized as either major or minor defect. The extent of crack of the major defect is more visible than the minor defect. The features extracted are shown in Appendices A and B .

DEFECTS	CHARACTERISTICS
Broken corners and edges	Physical damages on corners and edges
Colour grading	Changes in colour shades
Cracks	Thin and long random physical defects

Dirt	Small random particles on the surface
Drops	Include colour and water drops
Lines	Wide visible direct lines on bottle surface, mostly result of production line bars

Table 1: Defects and their typical characteristics.

RESULT & CONCLUSION

The Back Propagation Neural Network

For the purpose of classification, a back propagation neural network is used to simulate the extracted features. The back propagation algorithm is used for this purpose. In order to train a neural network to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights (EW). In order words, it is used calculate how the error changes as weight is increase or decreased slightly. The back propagation algorithm is the most widely used method for determining the EW.

The algorithm computes each EW by first computing the EA, the rate at which the error changes as the activity level of a unit is changed. For output units, the EA is simply the difference between the actual and desired output to computer the EA for a hidden unit in the layer just before the output unit layer, we first identify all the weights between that hidden unit and the output units to which it is connected. We then multiply that weight by EAs of those output units and add the products. The sum equals EA for the chosen hidden units. After calculating all the EAs in the hidden layer just before the output layers, we can compute in like fashion the EAs for other layers, moving from layer to layer in a direction opposite to the way activities propagate through the network. This is what gives back propagation its name. Once the EA has been computed from a unit, it is straight forward to compute the EW for each incoming connection of the unit. The EW is the product of the EA and the activity through the incoming connection.

Training and Simulation

To make a neural network that performs some specific task, we must choose how the units are connected to one another and we must set the weights on the connections appropriately. The connections determine whether it is possible for one unit to influence another. The weights specify the strength of the influence.

We can teach network to perform a particular task by using the following procedure:

1. We present the network with training examples, which consist of pattern of activities for the input units together with the desired pattern of activities for the output units.
2. We determine how closely the actual output of the network matches the desired output.
3. We change the weight of each connection so that the network produces a better approximation of the desired output.

CONCLUSION

The human brain is an excellent classifier that can successfully classify objects in noisy environments even without significant features. However, we still cannot expect the same performance from our artificial classifier. Therefore, to work towards a successful

classification, extracted features of the bottled images must show adequate separation in feature space. The artificial neural network approach has been used to detect the surface cracks in the bottles.
I described the basic approaches to digital image processing which is the first step in the research work. The extracted features set were then trained using a back propagation neural network. The data sets were simulated using Matlab Technical Computing Software.
After the simulation process, it was observed that the simulated output was very close in value to the target output of the extracted feature data sets. The error rate was very minimal and this shows that the back propagation neural network is a reliable classifier in machine vision. Although it carries a significant shortcoming, it relies on a lengthy training stage; irrespective of this it is still a reliable classifier.

RECOMMENDATIONS

The field of machine vision is still in its infancy stage in most under developed countries in the world, considerate efforts needs to be dedicated in solving problems of image recognition and processing.
To overcome the shortcomings of the back propagation classifier, research work is needed to get a classifier with short training stage knowing well that "Time" is an important factor in image processing.

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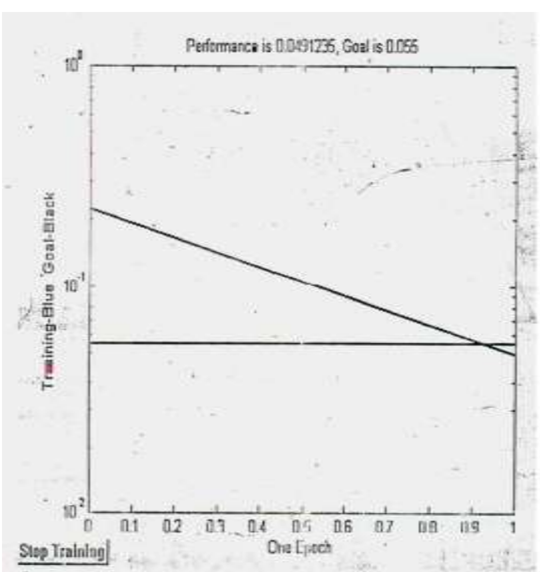

FIGURE 4: GRAPH SHOWING THE PERFORMANCE OF THE TRAINED EXTRACTED DATASET OF MINOR DEFECTS.

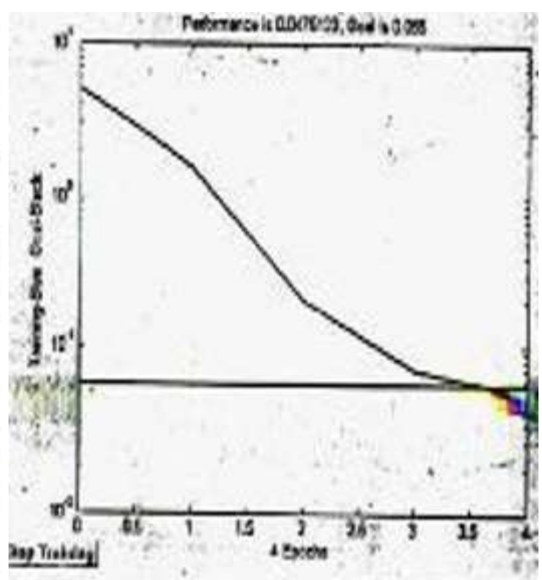

FIGURE 5: GRAPH SHOWING THE PERFORMANCE OF THE TRAINED EXTRACTED DATASET OF MAJOR DEFECTS

APPENDIX A: EXTRACTED FEATURE DATASETS OF MINOR DEFECTS

Defect	Area	Major Axis Length	Minor Axis Length	Equivalent Diameter	Extent
1	64	71.925	11.069	9.027	0.072
2	72	83.53	6.761	9.575	0.1
3	74	77.75	15.553	9.707	0.064
4	48	48.041	16.921	7.818	0.062
5	45	54.167	8.745	7.569	0.071
6	91	101.66	15.093	10.764	0.068
7	56	62.565	5.972	8.444	0.173
8	64	73.833	7.77	9.027	0.102
9	91	97.247	27.953	10.764	0.043
10	37	42.824	1.799	6.864	0.206
11	55	66.943	8.567	8.368	0.067
12	96	107.32	15.539	11.056	0.047
13	88	95.116	23.459	10.585	0.045
14	80	88.09	13.217	10.093	0.043
15	92	88.511	20.363	10.823	0.032
16	48	55.377	7.183	7.818	0.128
17	62	69.467	6.928	8.885	0.153
18	26	29.716	2.227	5.754	0.26
19	24	27.714	1.377	5.528	0.5
20	60	64.306	7.728	8.74	0.15
21	47	54.285	8.639	7.7736	0.143
22	65	71.94	10.119	9.097	0.09
23	87	92.279	15.7	10.525	0.073
24	48	52.083	10.928	7.818	0.054
25	105	112.34	28.119	11.562	0.039
26	75	80.667	16.313	9.772	0.056
27	69	77.938	24.104	9.373	0.054
28	55	62.842	10.073	8.368	0.085
29	85	98.793	9.5	10.403	0.091
30	66	76.587	8.644	9.167	0.777
31	27	31.177	1.155	5.863	1
32	75	82.534	18.222	9.772	0.06
33	64	70.089	12.58	9.027	0.076
34	67	77.46	12.996	9.236	0.064
35	29	32.383	4.691	6.077	0.159
36	68	74.032	12.719	9.305	0.08
37	27	31.177	1.155	5.863	1
38	59	68.276	10.27	8.667	0.111
39	61	67.635	14.509	8.813	0.075
40	52	56.303	8.707	8.137	0.046
41	58	65.07	10.383	8.593	0.061
42	68	78.585	7.529	9.305	0.091
43	35	39.268	3.237	6.676	0.141
44	61	66.238	15.551	8.813	0.55
45	60	82.05	7.829	8.74	0.026
46	65	73.603	17.656	9.097	0.068
47	68	73.864	8.266	9.305	0.065
48	34	42.331	2.883	6.58	0.052
49	63	66.817	11.446	8.956	0.0053
50	79	91.786	19.802	10.029	0.032

APPENDIX B: EXTRACTED FEATURE DATASETS OF MAJOR DEFECTS

Defect	Area	Major Axis Length	Minor Axis Length	Equivalent Diameter	Extent
51	500	114.6	5.911	25.231	0.556
52	752	649	5.793	30.943	0.83
53	508	134.28	5.155	25.432	0.139
54	540	145.27	5.074	26.221	0.166

55	568	159.38	8.962	26.892	0.377
56	552	127.65	5.876	25.511	0.452
57	588	135.74	5.803	27.362	0.831
58	360	100.69	4.891	21.409	0.409
59	832	190	5.942	32.547	0.315
60	657	123.7	66.517	28.923	0.084
61	571	135.77	5.508	26.963	0.092
62	364	101.83	4.893	21.528	0.409
63	730	165.45	5.987	30.487	0.137
64	364	94.035	5.253	21.528	0.128
65	643	146.44	5.966	28.613	0.316
66	466	112.62	5.63	24.358	0.103
67	540	125.81	5.819	26.221	0.11
68	808	207.43	5.324	32.075	0.05
69	911	203.19	59.663	34.058	0.063
70	333	75.766	5.968	20.591	0.459
71	368	98.19	5.098	21.646	0.096
72	432	99.637	5.87	23.453	0.148
73	563	128.79	5.938	26.774	0.457
74	447	109.87	5.531	23.857	0.1
75	910	126.95	57.473	34.039	0.126
76	591	148.68	5.417	27.431	0.071
77	647	158.81	23.969	28.702	0.073
78	476	118.81	5.516	24.618	0.09
79	672	154.13	5.922	29.251	0.501
80	474	122.99	5.324	24.567	0.081
81	299	81.173	5.046	19.511	0.115
82	753	146.39	40.275	30.964	0.103
83	602	162.74	5.077	27.686	0.059
84	514	139.9	4.956	25.582	0.067
85	590	159.72	5.866	29.64	0.093
86	622	143.66	5.876	28.142	0.622
87	486	125.6	5.261	24.876	0.091
88	512	118.22	5.801	25.532	0.828
89	576	131.29	5.96	27.081	0.361
90	569	145.37	5.394	26.916	0.071
91	710	101.74	13.294	30.067	0.477
92	470	123.5	5.196	24.463	0.081
93	420	109.8	5.204	23.125	0.143
94	470	112.58	5.721	24.463	0.106
95	628	181.35	4.748	28.277	0.497
96	972	224.83	5.878	35.179	0.312
97	398	109.16	4.979	22.511	0.279
98	832	190.89	5.915	32.547	0.456
99	450	128.37	4.803	23.937	0.402
100	828	188.93	5.946	32.469	0.297