Application perspectives for the Convolutional Downward Spiral Architecture

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Abstract: Adaptive learning is an important neural network characteristic; this means that they learn how to take care of difficult tasks by learning through illustrative samples of the problem to solve. Since neural networks can learn to tell the difference among many patterns by samples and training, there is no need to elaborate an a priori model, neither to develop specific probability distribution functions. This work presents the application results of a new architecture based on convolutional neural networks, named Convolutional Downward Spiral Architecture (CDSA), that generates digital filters automatically, which can be applied in a wide range of inspection systems.

Key–Words: Convolutional networks, digital filters, artificial vision, inspection processes

1 Introduction

To be competitive in today's manufacturing most automatic quality measuring systems have to be flexible, fast and reliable; which are characteristics that artificial vision systems gather.

Neural networks are being successfully applied in inspection processes due to their proven characteristics for this purpose. Lee et al. [10] used neural networks for defects classification by energy and entropy characteristics on pieces of iron images. Stojanovic et al. [16] proposed a mixture of inspection techniques based on binary images processing, statistical analysis and classification with neural networks, in a textile products inspection system. Campoy et al. [4] proposed applying digital filters automatically generated by neural networks on paper pulp inspection, subsequently, Calderon and Campoy [1], [2] have recently proposed an architecture using convolutional neural networks for the same purpose.

1.1 Convolutional Neural Networks

Convolutional neural networks provide an efficient method for restricting complexity in feed-forward networks by sharing weights and restricting local connections. This topology has been applied to image classification when sophisticated preprocessing has to be avoided and the direct classification of raw images is needed.

The first implementation of a Convolutional Neural Network can be considered the Fukushima's neocognitron[5]. There exist many possibilities to design a convolutional neural network architecture, by combining different types of neurons and learning rules. The number of layers and groups in each layer depends on the application.The learning process in a convolutional network is based on the back-propagation algorithm, that updates the neuron's weights w

$$w(t+1) = w(t) + \eta\delta(t)x(t) \quad (1)$$

where η is the learning rate, $x(t)$ is the input to the neuron, and $\delta(t)$ is the error term for the neuron.

There have been developed applications using convolutional neural networks in many areas, such as character recognition (printed and manually written) by LeCun [9], visual document analysis by Simard et al [15], face recognition by Lawrence [7], [8], medical image analysis by Lin [11] and Sahiner et al [13], and car detection by Matsugu and Cardon [12].

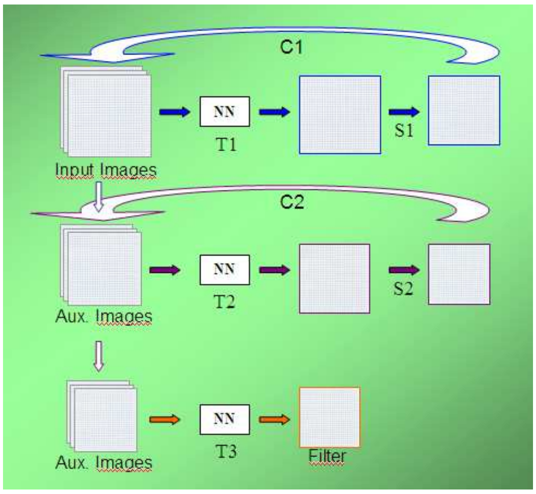

Figure 1: Convolutional Downward Spiral Architecture.

2 The Convolutional Downward Spiral Architecture

The *Convolutional Downward Spiral Architecture* (CDSA) shown in figure 1 has been designed and used for generating digital filters and as a matter of demonstration a set of filters have been applied in a paper pulp inspection process.

The neural network is trained off line using images with defects which type depends on the filter that the user wants to obtain, as well as images without defects.

The coefficients of the convolutional filters are developed by the neural network throughout the back-propagation training algorithm.

As it can be observed in figure 1 the algorithm is fed with 30x30 pixel images, which are used to train (T1) a neural network obtaining a coefficients matrix of similar dimensions, then a sub-sampling (S1) is performed, generating a 28x28 pixel mask which is used to carry out convolutions (C1) over the original images in order to obtain auxiliary images better centered than the originals according to the highest response obtained with this mask. The process is repeated many times in a downward spiral shape until the filter is obtained, with the minimum limit being the defect size of the desired filter.

3 An application of the CDSA

During the paper pulp production, defects inherent to the process appear, they are impurities which do not respond to certain pattern, and

Table 1: Defect types

Type	Size, mm^2
E	0.08
D	0.20
C	0.45
B	0.80
A1-A7	1.0-5.0

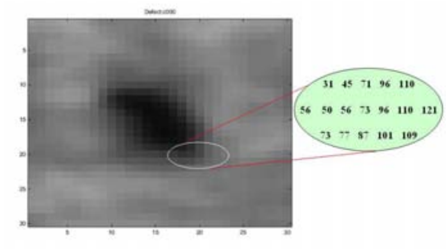

Figure 2: Intensity values around a defect neighborhood.

arose from different origins. There are two kinds of defects called *pitch* y *shive*, which are classified in various types according to their size, as can be observed in table 1, obtained from a specific factory. The defects generated do not show fixed schemes in their arrangement, and look darker with respect to their neighborhood.

It can be seen in figure 2 a defect example and the intensity values around the defect neighborhood.

Some aspects to know about these kinds of defects are:

- They have not well defined geometric shapes,
- In general they present the same gray level, although some of them are lighter and can be misclassified,
- Rugosity of the paper pulp may vary so that the mean and standard deviation also vary,
- There exist a great variety among defects of same type, and similarity among defects of different type.

These mentioned aspects can be observed in figures 3 and 4.

3.1 The system phases

The system has two phases, fully described in Calderon and Campoy [1], [2], [3], during the first phase the digital filters are generated by means of the CDSA, and in the second phase the filters are

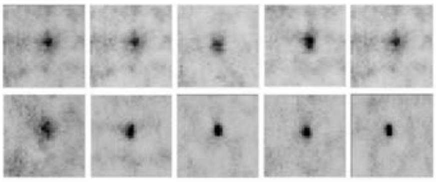

Figure 3: Similarity among defects of different type (D and C).

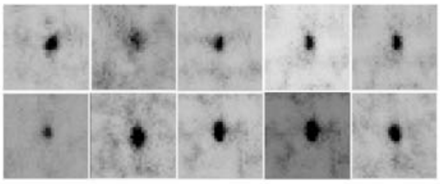

Figure 4: Variety of same type defects (C).

used in order to detect and classify different types of defects.

3.1.1 Filters generation phase

Automatic generation of digital filters is a phase that involves the steps shown in figure 5.

3.1.2 Inspection process phase

Inspection is the second phase of the system and it is shown in figure 6, which implies detection and identification of defects.

4 Results

The proposed methodology has been applied to several paper pulp samples. Figure 7 shows an example of the response obtained when filters for detecting C and D defect types are applied to samples with B, C, D, and E defect types and samples with no defects.

In the following confusion matrix shown in table 2 it can be observed the number of correct responses to the developed filters. On the table Det. means Detected, and def. defective.

The overall results shown in table 3, demonstrates a good performance of the filters developed.

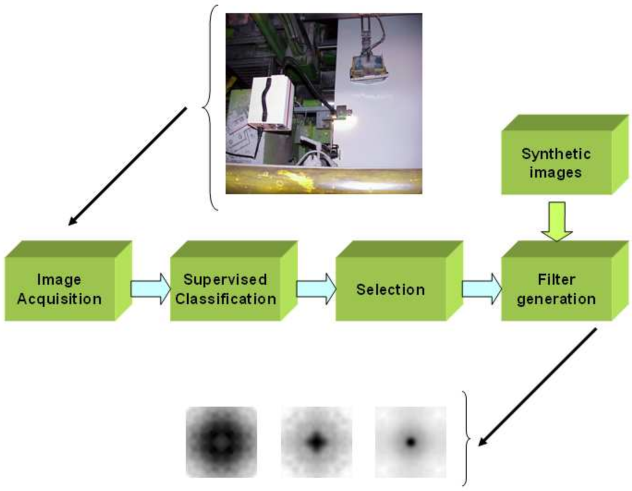

Figure 5: Generation of digital filters process.

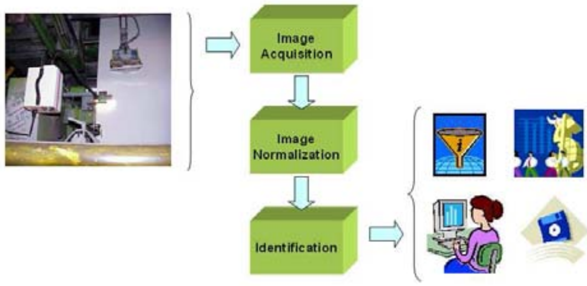

Figure 6: Inspection process.

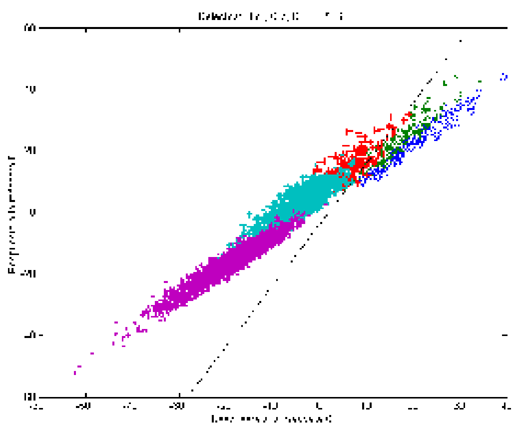

Figure 7: Response to C and D filters for different defect types.

Table 2: Confusion matrix

Defect type	Det. as B	Det. as C	Det. as D	Det. as E	Det. as Non def.
B	60	10	0	1	0
C	37	159	8	0	0
D	1	28	275	30	0
E	0	1	42	482	1
N	0	0	0	0	500

Table 3: Percentage of identification for a test set

Defect type	Total samples	Correct identification	Percentage
B	71	60	84.50
C	204	159	77.94
D	334	275	82.33
E	525	482	91.80
N	500	500	100.00

5 Perspectives for the CDSA

The four aspects mentioned on Section 3 have a similar effect in other environments

Given the generality of the presented architecture, it can be applied in other manufacturing environments as well as in different inspection and diagnosis activities, such as medical, where many authors [6], [14] have worked on.

Figure 8 shows examples of different materials that can be inspected or analyzed by using the methodology studied here.

An interesting manufacturing process where this methodology would be used is in the leather products in an industry located in Mexico. A vision system for leather inspection based upon visual characteristics of the material surface could be developed. As visual appearances of both leather and defects exhibit a wide range of variations due to original skin characteristics, curing processes and defect causes, location and classification of defective areas become hard tasks, so that an automatic inspection system is desirable to be used.

Figure 8: Examples of different materials.

6 Conclusion

This paper presented a methodology for generating digital filters automatically, which have been applied in a paper pulp inspection process. The methodology is based on a convolutional neural network architecture, that builds up specific filters for particular defect types.

Satisfactory results have been obtained from a convolutional neural architecture, which generates digital filters that have been tested over images with and without defects obtained at a paper pulp plant, at normal production conditions. The system even achieved a faster detection rate than an experienced operator.

This architecture can be applied in automatic inspection processes in diverse manufacturing environments. Ongoing work also includes experiments with other materials, such as ceramic and wood, and hopefully soon human tissues.

References:

[1] J.A. Calderon-Martinez, and P. Campoy-Cervera, A Convolutional Neural Architecture: An Application for Defects Detection in Continuous Manufacturing Systems, *ISCAS'2003 IEEE International Symposium on Circuits and Systems Proceedings*, May 2003, Bangkok, Thailand.

[2] J.A. Calderon-Martinez, and P. Campoy-Cervera, Defects Detection in Continuous Manufacturing by means of Convolutional Neural Net- works, *IWANN'2003 7th International Work-Conference on Artificial and Natural Neural Networks*, Menorca, Spain, June 2003. Proceedings, pp. 528-535.

[3] J.A. Calderon-Martinez, and P. Campoy-Cervera, An application of Convolutional Neural Networks for Automatic Inspection, *IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and Robotics, Automation and Mechatronics (RAM)*, Bangkok, Thailand, June 2006. Proceedings, pp. 345-352

[4] P. Campoy-Cervera, D.F. Munoz-Garcia, D. Pena, and J.A. Calderon-Martinez, Automatic Generation of Digital Filters by NN Based Learning: An application on Paper

Pulp Inspection, *IWANN'2001 6th International Work-Conference on Artificial and Natural Neural Networks*, June 2001, Proceedings, pp. 235-245

[5] K. Fukushima, Neocognitron: A self organizing neural-network model for a mechanism of pattern recognition unaffected by shift in position, *Biological Cybernetics*, vol. 36, pp. 193-202, 1980.

[6] C. Kwak, J.A. Ventura, and K. A. Tofang-Sazi, Neural network approach for defect identification and classification on leather fabric, *Journal of Intelligent Manufacturing*, 11(5):485-499, October 2000.

[7] S. Lawrence, C.L. Giles, and A.C. Tsoi, Convolutional neural networks for face recognition, 1996. *Proc. CVPR '96 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 217-222, 1996.

[8] S. Lawrence, C.L. Giles, A.C. Tsoi, and A.D. Back, Face recognition: A convolutional neural-network approach, *IEEE Transactions on Neural Networks*, vol. 8, n 1, pages 98-113, 1997.

[9] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-Based learning applied to document recognition, *Proceedings of the IEEE*, Nov. 1998, pp. 1-45.

[10] C.S. Lee, C.H. Choi, J.Y. Choi, Y.K. Kim, and S.H. Choi, Feature extraction algorithm based on adaptive wavelet packet for surface detect classification, *IEEE International Conference on Image Processing*, 1996, pp. 673-675.

[11] J.-S. Lin, P.A. Ligomenides, S.-C- B. Lo, A. Hasegawa, M.T. Freedman, and S.K. Mun, An Application of Convolution Neural Networks: Reducing False-Positives in Lung Nodule Detection, *IEEE Nuclear Science Symposium and Medical Imaging Conference*, 1994. vol. 4, pages 1842-1846.

[12] M. Matsugu, and P. Cardon, Unsupervised Feature Selection for Multi-class Object Detection Using Convolutional Neural Networks, *International Symposium on Neural Networks*, Dalian, China, August 2004, Proceedings, Part I, pp. 864 - 869.

[13] B. Sahiner, H.P. Chan, N. Petrick, D. Wei, M.A. Helvie, D.D. Adler, and M.M. Goodsitt, Classification of Mass and Normal Breast Tissue: A Convolution Neural Network Classifier with Spatial Domain and Texture Images, *IEEE Transactions on Medical Imaging*, Vol. 5, pp. 598-610, Oct. 1996.

[14] O. Silven, M. Niskanen, and H. Kauppinen, Wood inspection with non supervised clustering, http://www.ee.oulu.fi/olli/Projects/Lumber.Grading.html

[15] P.Y. Simard, D. Steinkraus, J.C. Platt Best Practices for Convolutional Neural Networks Applied to Visual Document Analysis, *7th International Conference on Document Analysis and Recognition*, 3-6 August 2003, Edinburgh, Scotland

[16] R. Stojanovic, P. Mitropulos, C. Koulamas, Y. Karayiannis, S. Koubias, and G. Papadopoulos, Real-Time Vision-Based System for Textile Fabric Inspection, *Real-Time Imaging 7*, Academic Press, pp. 507-518, 2001.