

## A Neural Network Based Method for Automated Classification of Sheep Leather Images

Jianqin Liu, Nanning Zheng, Li wei and Qingyuan Wang

Xi'an Jiaotong University, Institute of AI & Robotics  
Xi'an, P. R. China, 710049

### ABSTRACT

This paper proposes a new method for automated classification of sheep leather images according to their textures, based on the simultaneous autoregressive (SAR) model and multi-layer BP neural network. The method described which consists of three steps: (1) SAR modelling and parameter estimation; (2) Feature extraction and learning through samplers; and (3) Three-layer BP net based classification, can effectively explore the leather textures characterized with heavy irregularity of texture elements, less separability of clusters which is difficult for conventional methods to cope with.

### 1. Introduction

In leather clothing industry, the recognition and classification of leather is usually handled solely by the eyes of technicians with long term experiences, which is an exhausting work. In order to get rid of such burden and improve efficiency and accuracy, it was suggested that machine vision technique could be applied and the automated classification system for natural leather images be constructed.

In recent years, the textured image modelling, analysis and recognition techniques have been applied in many industrial fields. In the view of signal processing, the image texture processing techniques could be classified as two categories: spatial and frequencial techniques, while in the view of pattern recognition, it could be grouped into two parties too: statistical clustering and grammar inference, in which the statistical method is with strong adaptability.

In the automation machine for leather texture analysis, the existing difficulties, which have been faced by the reserachers, could be dedicated as the following four respects:

- (1) The textel (texture element) of the sheep leather is rather irregular.
- (2) The traditional statistical techniques such as Fourier transformation are not efficient and exact in the case.
- (3) For its requirement of certainty, traditional mathematical model could not represent the leather texture pattern.
- (4) The classical classification operations depend mainly on human experiences and to obtain the necessary knowledge needs to practise for many years.

With the hypothesis that the difficulties could be conquered by the adaptive random field modeling and the neural network mechanism, the texture classification method discussed in this paper, extracts the efficient statistical texture features that satisfied certain within-class invariance and inter-class separation by the parameter estimation of SAR random field modelling. The optimal classification is implemented by three-layered BP network in Bayesian meaning, which is a neural classifier with self-learning function, and could be used to perform the self-adaptive classification and the uncertainty knowledge learning procedure, moreover, the classification method is useful in describing the random texture pattern formally and acquiring uncertain experienced knowledge therefore could be regarded as a practical natural textured image analysis method.

Materials used in the experiments are natural sheep leather materials provided by factories in leather clothing industry. The experiment results show that the method could lead to an efficient and practical technique of natural texture analysis applications with the neural network principle and the machine vision tools.

### II. Summary of the algorithm

Belonging to the set of statistical textured classification, the algorithm is composed of the following steps: (1) SAR modelling and parameter estimation; (2) Feature extraction and sampler learning; (3) Neural network based classification procedure (Shown in figure 1). Owing to the parallel structure of both the BP network and the algorithm of SAR parameter estimation, the method is also with such a advantage hence is convenient for being implemented on computer. The combination of the pattern depiction exhibiting the statistical fetures of models and artificial neural network entitles the algorithm several unusualness: (1) More feasibility. It possesses the potent of analysing some textures with much irregularity and similarity in general patterns that are difficult for conventional way. (2) With its adaptivity and self-learning, the inference of the algorithm can simulate the correspondent process of human being, especially fuzzy inference and associative memory, therefore it may assist to solve such problems that precise logical deduction is unsuitable to describe and to solve.

(3) The system can obtain and store knowledge expressed hiddenly through the training of weights and exemplar learning so that it can be applied to adaptive clustering and recognition.(4) The parallel distributed structure of the system expresses the principle of intellectual organization of information processing to some extent.

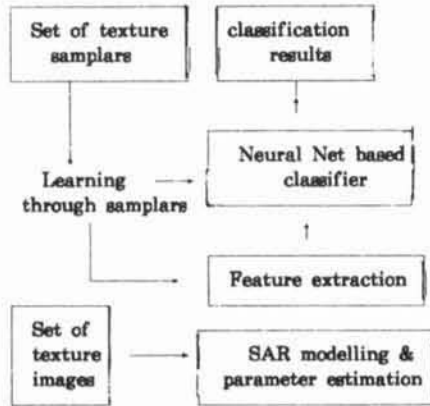


Figure 1. Structure of the algorithm

### 3. SAR modelling and parameter estimation

In the paper, a so called simultaneous autoregressive (SAR) model which is two dimensional and noncausal is adopted aiming at expressing the relating property of spatial texture. Differing from some previous methods [1, 2], we took statistical values as texture feature which is comparatively stronger in classification and has been used in the consequent process.

Let  $\{g(x,y); x,y=0,1,\dots, M-1\}$  represent an image of  $M \times M$  gray value pixels, if the image satisfies the condition of SAR model defined in  $M \times M$  arrays, then

$$g(x,y) - u_m = \sum_{i,j \in N} O(i,j) [g(x \odot i, y \odot j) - u_m] + \sqrt{p_n} w(x,y)$$

where  $u_m$  is exemplar average of pixel values;  $N$  is neighbour set defined on spatial domain excluding point  $(0,0)$ ;  $o(i,j)$  stands for the model parameters showing the relationship between a pixel and its neighbours; in symmetry space, we have  $\{o(i,j), o(-i,-j) \in N, o(i,j) = o(-i,-j)\}$ ;  $\odot$  means to make the sum modulo  $M$ ;  $w(x,y)$ s are independent, identically distributed Gaussian random variables with zero mean and unity variance, which show the random property of the pattern;  $p_n$  is the total variance of noise measuring the stochastic property of textures.

With the maximum likelihood estimation of the SAR model, a set of parameters could be extracted,

we chose  $\{c(-1,0), c(0,-1), c(-1,-1), c(-1,-1)\}$  to make the character vector.

### 4. Multi-layer BP net based classification

Among the neural net based classification algorithms, the multi-layer perceptron (BP net) is most outstanding because of its ability of adaptive optimum classification. After learning through a finite set of exemplars, the system can alter the connective weights within it

automatically, in addition with associative memory. Less constrained by the types of texture and conditions on grasping the image, multi-layer BP net can achieve classification of many texture patterns. Using the four dimensional vector discussed above as the input of the network, the statistical classification and recognition in Bayesian meaning can be put into practice.

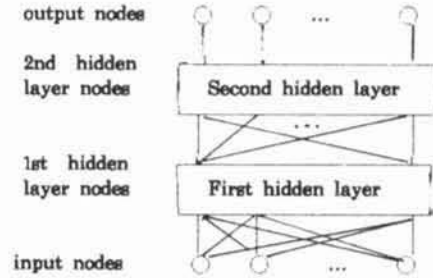


Figure 2. Structure of 3-layer BP net

### 4.1 The structure of the neural net

The algorithm proposed takes a BP net with 3 layers, as shown in figure 2.

Input nodes: the pattern vector is of four dimension,  $u_i (i=1,2,3,4)$ .

Output nodes:  $y_i (i=1,2,\dots,M)$ ; in which  $M$  is the index of feature class).

Hidden nodes: The network has two hidden layers. The number of hidden nodes is related to the complexity of the classification and the weights connecting the nodes involving the information of constraint and hidden knowledge.

### 4.2 Classification algorithm

While the weights already adapted by training, the network takes the following operation:

In the first hidden layer,  $u_j = f(\sum W_{1,j} u_i)$ ,

$1 < j < H_1$  ( $H_1$  is the number of nodes in the first layer);

In the second hidden layer,

$$u'_k = f(\sum W'_{2,k} u_j)$$

$1 < k < H_2$  ( $H_2$  is the number of hidden nodes in the second layer);

In output layer,  $y_l = f(\sum W''_{l,k} u'_k)$ ,

$$1 < l < M.$$

The classification result then is correspondent to the active output node  $y_l (1 < l < M)$ , that is, the input is to be assigned to class  $l$ . In the above process  $f(a) = 1/(1+e^{-a})$ , in which  $W_{1,j}$  is an element of the weight matrix between the input layer and the first hidden layer while  $W'_{2,k}$  and  $W''_{l,k}$  are similarly members of matrix between the two hidden layers or between the output layer and the second hidden layer respectively.

### 4.3 The process of training and knowledge acquiring

Before trained the connective weights of the neural network were set to minor random values, then the system was fed with carefully selected exemplars, and the net was altered according to the difference of the real output and the desired one, in another word, the weights were repeatedly changed in the way of decreasing gradients until the system converges. In the experiment of sheep lather image classification,

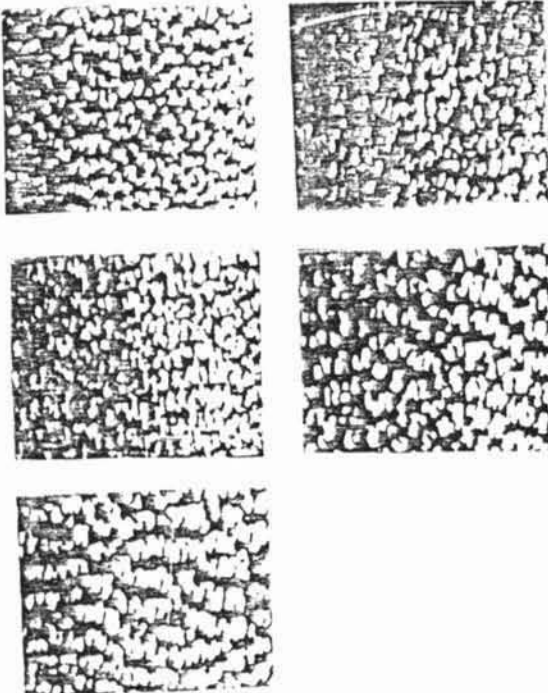
the size of training set is 94 which has been proved by the experiment to be sufficient.

The learning system of BP net is effective in that during supervised drilling procedure, it can achieve getting knowledge automatically, furthermore the knowledge storage of the network will be improved with the expansion of semantics of exemplar set. In such parallel distributed processing and storing system of information, the weights after the process of network learning from typical samplers, present both the identity of similar samplers within the accuracy permitted by the system and the difference between different samplers. Such structure is not only convenient for knowledge expression but also for its acquirement. In conventional techniques of expert system, the way of knowledge expression such as semantic net, generating rules are too much limited by inference with certainty, thus can not describe pattern feature of leather texture effectively, whereas the field is exactly where neural network featured by uncertainty inference, associative memory and intelligent simulation, shows its advantage most.

#### 5. Experiment result

The algorithm has been simulated on SUN-80386 micro computer with TURBO-C. All texture image data are sheep leather texture pictures, which labeled with  $z_1, z_2, z_3, \dots, z_7$ , of which correspondent texture features and classification results are shown in chart 1. From the results, it can be concluded that the classification completed by computer and that by experienced worker lead to the same results, that means the algorithm has the satisfying adaptivity.

The neural net based leather classification system is composed of the following five parts as: picture grabber, image input subsystem, image preprocessing and feature extraction block, neural net classification subsystem and results display equipment.



No.	Features( $\times 10^{-3}$ )				result
	$o(-1,0)$	$o(0,-1)$	$o(-1,1)$	$o(-1,-1)$	
$z_1$	6.210	-37.730	8.872	-27.049	class1
$z_2$	-15.87	-48.476	8.699	-36.413	class2
$z_3$	-15.226	-48.949	-5.782	-37.718	class2
$z_4$	-12.279	-48.400	-2.686	-36.148	class3
$z_5$	-12.830	-45.905	-4.729	-29.159	class3
$z_6$	9.321	33.667	28.651	-21.938	class4
$z_7$	-8.019	-48.020	5.205	-33.069	class5

Chart 1. Texture feature and classification result

#### 6. Conclusion

The algorithm of neural network based classification of leather texture proposed in the paper possesses following characteristics: (1) It can assign an input of texture to the most suitable cluster under Bayesian meaning; (2) The distribution of weights express quite well the property of both the whole structure and each class. The algorithm can classify sheep leather effectively owing to the important role taken by neural network's highly adaptivity, self organization, self-learning and associated memory. Consequent work will lay stress on the expedition of BP net's convergence, expansion of knowledge containment and the development of parallel hardware system. As we are getting more experient, the processing extent and adaptivity of the system are sure to improve further.

#### 7. Acknowledgement

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#### 8. References

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