HYBRID SYSTEM OF EXPERT SYSTEM AND ARTIFICIAL NEURAL NETWORKS FOR OBJECTIVE EVALUATION OF PRODUCT SENSUOUS QUALITY

Zhenwei Su*, Daizhong Su**

Basic problems and the bottleneck of current approaches for objective assessment of product sensuous quality (PSQ) are discussed. As a solution, a new approach, an expert system (ES) based on artificial neural networks (ANNs) is proposed, in which the ES and ANNs co-operate in a superiority compensation way. The knowledge base of the system can be effectively built and the evaluation of PSQ can be conducted on-line. As a case study, the new approach has been applied in leather handle test and it proves that the approach is capable of handling non-linear relationships among multiple measured PSQ parameters.

Key words : *product sensuous quality, expert system, artificial neural networks, subjective assessment, objective evaluation*

1. Introduction

Some qualities of some products, such as handle of cloth and leather, odour of perfumery, taste of beverage and food, are mainly assessed by personal sense and experience, but not by instruments. In this paper, this kind of qualities is defined as product sensuous qualities (PSQ). The traditional methods of assessing PSQ are sensory, which are fast, simple and on-line, using adjectives such as 'wonderful', 'better', 'good', 'bad', 'soft', 'hard', and so on to describe personal sensory perception. These subjective assessment methods have been used for a long time throughout the world, and have been accepted by both industry and consumers, due to the reason that they can satisfy at least some of the requirements of practical production and trading, and partly because of the reliability of the handle, odour, taste and image phenomenon within specific ranges (for certain kinds of people, products and end-use). However, the results of the subjective assessment are fuzzy, which can not be used in auto-control. And there is poor agreement among those who use these adjectives because of the differences of their cultural background [1].

In recent years, research into the objective measurement of PSQ has drawn great attention, due to the increasing demand for PSQ assessment on the market, and the advances in use of computers and auto-control technology in the manufacture process of PSQ related products such as leather, beverage, etc. In the literature, several methods for objective evaluation of PSQ have been proposed [2], [3], [4]. However, three basic problems still remain to be resolved :

1) Subjective assessment of PSQ represents an aesthetic conception, a reflection of personal sensory preferences. For example, 'handle' means the sum total of the sensa-

* Z. Su, Department of Engineering, University of Wales College, Newport, Newport, NP9 5XR, UK
** Department of Mechanical and Manufacturing Engineering, Nottingham Trent University, Burton Street, Nottingham, NG1 4BU, UK

tions expressed when a cloth or leather is handled by touching, flexing, and smoothing. Obviously, for different markets, different producers, and consumers with different backgrounds, the subjective assessment results for the same goods are diverse and, in extreme cases, even opposite [5]. Due to this diversity, it is necessary to derive a data processing method to adapt the various relationships between sensory stimuli and different personal responses.

2) It is widely recognised that the stimuli leading to the psychological responses of PSQ is determined by the physical or chemical properties of the assessed samples. The traditional methods for evaluation of those samples are to measure their physical or chemical properties, then use multivariate regression to relate the subjective assessment results, which are given by experts, to the objectively measured data; then formulate the equations to calculate the evaluating results as shown below [6], [7].

$$S = \sum K_i R_i + K_0 \ ,$$

where, S – subjective assessment value, R_i – the ith objective measure data, K_i – the ith weighting factor, K_0 – an constant.

One problem of the approach is that the validity of multivariate regression analysis is influenced by correlativety of data, which appears to exist between the physical or chemical parameters of tested samples. Another problem of the approach is that the S, a fuzzy result of subjective assessment, is expressed in a precise value and driven from precise calculation in classically mathematical theory. As a result, the values of the parameters such as Ki and K0 within the equation derived from some cases may be not satisfactorily applicable to other cases.

3) There is poor agreement between replicate test results of physical or chemical properties for certain products, even those tests conducted under the same measurement conditions. For example, leather is a visco-elastic material and its physical properties change with temperature, humidity and atmospheric pressure; while the chemical components of perfumery, beverage and food change with temperature, storage time and other factors. Their reproducibility of test results are so poor that it is necessary to develop a data processing approach which could provide a great degree of robustness or fault tolerance.

In recent years, some pattern recognition methods, including widest range cluster, narrowest range cluster, weight cluster, fuzzy cluster and so on have been suggested for evaluation of handle of cloth and fibre [8]. The test data show that the agreement of subjective assessment and objective evaluation depends on the selection of the features in the cluster [9]. So far, the bottleneck problem- selection of the features in the cluster, has not been broken yet.

As a powerful tool, expert systems have been used to resolve various non-linear problems, which are characterised by fuzzy and experience [10]. However, to use an expert system for PSQ on-line test, two problems have to be resolved [11]:

1) On-line test should be very fast; while the reasoning process of an expet system using production rules usually takes longer time than what required. This is due to the reasoning process in which the inference engine searches the whole ruler base for matching the condition of each rule, then solve the conflicts among those selected rules. Thus, before the result comes out, the system has made a lot of inefficient matching and calculation, and with the more deep the system infers, the more time it takes.

2) Assessment of PSQ is some kind of subjective reflection, which is mainly concerned with lower consciousness action, but not logical inference. Sometimes, the knowledge of experts is difficult to be expressed in words and is difficult to be written in a rule form. In particular, it is more difficult to determine confidence value for those fuzzy rules.

On the other hand, for ANNs, the reasoning is fast and the acquisition of expert knowledge is relatively easy, especially for fuzzy knowledge. It has been demonstrated that ANNs are capable of handling non-linear relationships and identifying which class best represents an input pattern, even the inputs have been corrupted by 'noise'. The main shortage of ANNs is time consuming for its training, and the more nodes the system consists of, the more time its training takes. In the objective evaluation of PSQ, the samples and their types are so complex that it requires huge ANNs which are difficult to be trained.

In this paper, a hybrid system of an expert system based on BP neural networks for on-line test of PSQ is presented. The expert system is used for rough classification and controls a group of ANNs; while the ANNs are used for fuzzy knowledge storage and fuzzy reasoning. The expert system and ANNs co-operate in a co-ordinate fashion to compensate each other. As a case study, the hybrid system is applied in objective evaluation of leather handle. The results obtained demonstrate that there is close agreement between the subjective assessment results of experts and the objective evaluation results of the system.
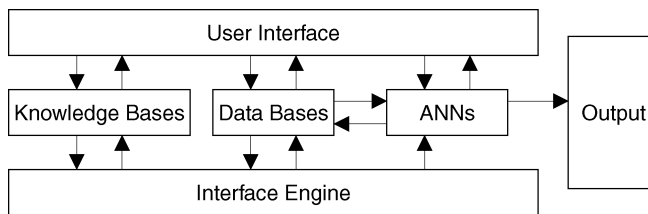

Fig.1: Main structure of the system

2. Structure of the system

The main structure of the system is shown in figure 1. The system consists of six modules : Knowledge Bases, Inference Engine, DataBases, ANNs, Output and User Interface. The knowledge bases consist of two parts : a production rule base and an ANNs parameter file base.

In the system, the inference engine runs in this way : before a rule is activated, the inference engine matches the condition and resolving the conflicts according to the matched rules' superiority. After a rule activated, the inference engine loads the parameter file of ANNs, then constructs the ANNs and runs the ANNs.

The input data to the ES are the measured parameters and sample types. The sample types are relevant to the sample end-use and assessment standards. The output of the ES is a command, which constructs ANNs from a structure parameter file, then it activates the ANNs.

The structure of ANNS is flexible. The layers of an ANN, the nodes in each layer and other structure parameters (training step length, system error, etc.) are determined by the user during ANN training, or specified using a parameter file selected by relevant production rules. The sigmoid function is used for the computational nodes and the back-propagation

learning rule is employed to find the most suitable weights for the network [12]. After training, all the structure parameters and weights between nodes are saved in a parameter file.

The flow chart of the BP ANNs training is shown in figure 2. The function of set up module is to configure the structure parameters of ANNs at the beginning of the training. It consists of two parts : one for ANNs training, the other is for pattern recognition. In the first part the user inputs the ANNs parameters in a dialogue form, including the number of layer, the number of nodes in a layer, learning rate, momentum rate, maximum total error, individual error and the maximum number of iteration. At the beginning of training, the weight parameters of ANNs are automatically produced by a random function. In the second part of the set up module, the structure parameters of an ANNs come from the loaded parameter file by the activated production rule.
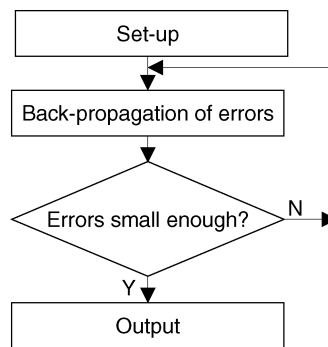

Fig.2: Flow chart of BP ANNs

The training set is inputted in a matrix form. In the training, after the maximum number of iteration or the individual error is reached, the system will output the training maximum total error, the individual error and number of iteration. Comparing with the training goal or last training results, the users can save the structure parameters and weights of the ANNs in a file or continue for the next training. In this way, with the time passes, the system becomes more and more 'cleaver'.

In the system, production rules control ANNs; and fuzzy knowledge is stored in the ANNs. The production rules come from logical knowledge of experts assessing the samples, which can be easily expressed in a symbol form and clear enough to be written down; while the ANNs store fuzzy experience in the assessment process, which is kept in the experts mind but difficult to be expressed in words.

In the subjective assessment of PSQ, comparing with fuzzy experience, logical knowledge is a small part. In addition, in the system, the function of ES is only to roughly classify the samples into groups; while, a huge number of fuzzy knowledge is stored in the parameter files of ANNs. So, the production rule base is rather small so that the system runs fast.

On the other hand, there are limited sample patterns in each group after rough classification by ES, and only a part of measured parameters is used as the input of ANNs. So, a small ANNs, which consists of a few number of nodes, could be successfully used for pattern recognition. As a result, the training time will be significantly reduced.

In addition, the above two types of knowledge have different storage forms and are acquired in different ways; there is no direct-relevance between the ANNs training and the ES. So, modifying one of them does not affect the other.

3. Case study

Handle is a most important measurement of leather properties. So far there have not been any instruments for leather handle test in leather industry. Due to the subjectivity and fuzziness of test of leather handle, the manufacturing of leather and leather goods has still been in handwork stage.

The recent research of leather handle test demonstrated that leather handle is mainly determined by the five mechanical properties : elastic property, friction force of a leather surface, flexibility property, thickness in natural condition and compressible property [13].

Experts can accurately assess leather handle by touching sense from their finger and palm, but they can not describe the relationship between the assessment results and the above five mechanical properties. Therefore, it is difficult to build an expert system to assess leather handle.

On the other hand, there are seven types leather : industrial leather, shoes leather, cloth leather, furniture leather, box leather, ball leather and other leather. And each type can be divided into several subtypes. For example, cloth leather can be divided into grain leather, suede leather, grove leather, and so on. And every subtype can be divided into several phyles, such as goat gain leather, pig gain leather ... and so on. Different types of leathers have different assessment standards for handle test. Generally speaking, good cloth leather is very soft and plentiful; while good shoe leather gives people a comfortable but different sensing. If ANNs are used to assess leather handle, huge number of nodes should be used for construction of ANNs because there are huge number of combinations between the leather types and the above five parameters. The training of ANNs would be very difficult.

In this paper, An expert system based on ANNs is used to objectively assess leather handle. The expert system is used to roughly classify the samples into groups. Leather type and thickness are chosen as the basic parameters. An example of the production rule within the ES is as follows :

```
IF the sample is [Shoe] leather
    AND is [Sheep] leather
    AND it's max. Thickness < [1.5mm]
    AND its min thickness > [0.4mm]
THEN load [s99 ] file
```

Here, the type name (i.e. Shoe) and subtype name of leather (i.e. Sheep) are chosen from the industry standard. In the condition of the above production rule, a group of sheep leathers is selected which is used for shoes making with thickness between $0.4\,mm$ and $1.5\,mm$. And, the ANNs parameter file 's99' contains the structure and all weights of the ANNs.

Before the production rules are activated, the ANNs should be trained. For the leather of this group, we choose fourteen samples of shoe leather and formed training set for the BP ANNs as shown in table 1.

Sample	Test 1 (N)	Test 2 (N)	Test 3 (N)	Test 4 (mm)	Test 5 (10%)	Subjective ranking
1	1.12	0.72	1.52	0.60	2.83	1
2	1.46	0.87	1.68	0.54	3.70	1
3	0.96	0.82	1.54	0.79	2.78	1
4	0.82	0.93	1.04	0.47	255	2
5	0.94	0.95	1.04	0.71	3.10	2
6	0.86	0.96	1.03	0.62	1.13	2
7	1.21	1.46	0.88	0.67	3.31	3
8	0.76	0.98	0.86	0.75	2.13	3
9	0.88	1.18	1.20	1.21	0.90	4
10	0.90	0.91	1.30	0.67	4.18	4
11	0.52	3.71	1.48	1.12	3.04	7
12	0.32	4.74	1.08	1.48	0.81	7
13	0.27	17.17	0.72	0.87	0.69	9
14	0.80	1.77	0.88	0.60	3.33	8
15	0.47	8.00	1.40	1.33	2.48	8

Tab.1: Training set for ANNs

Where : Test 1 – results of elastic test of leather, Test 2 – results of friction force test of a leather surface, Test 3 – results of flex test of leather, Test 4 – results of thickness test of leather, Test 5 – results of compress test of leather. The subjective ranking is a statistic meaning result, which comes from experts [13].

In the training, the values of the five parameters and the subjective ranking are the input of the ANNs in a matrix form. Comparing with the training errors after each training, the best structure of BP ANNs was finally determined which consists of 3 layers and 9 nodes, as shown in figure 3.

The learning rate is 0.89, the momentum is 0.79, and the individual error is 0.000003. All these parameters and weights of the nodes are saved in a file named as 's99'.
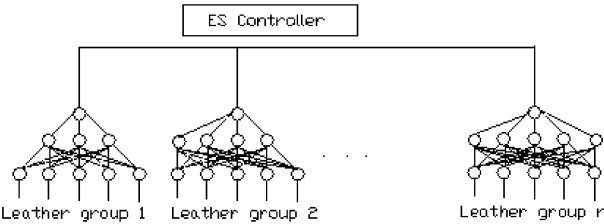

Fig.3: BP ANNs

To examine the pattern classifying ability of the system, nine samples are used. From the type name, subtype name and the leather thickness, the ES actives the above production rules. The rule loads the parameter file 's99', then constructs the ANNs and output the evaluation results as shown in table 2, where the objective result is the output of ANNs, which represents the objective ranking of leather quality.

Generally speaking, the agreement between subjective assessment results and objective measurement results is close. The results indicate that the system not only can memorise the input patterns (as sample 3 and sample 5) by training, but also can recognise the new patterns (as sample $16 - 22$) by associative memory.

Sample	Test 1 (N)	Test 2 (N)	Test 3 (N)	Test 4 (mm)	Test 5 (10%)	Subjective result	Objective result
3	0.96	0.82	1.54	0.79	2.78	1	1.06897
16	0.90	0.98	1.10	0.72	2.78	2	2.01141
18	0.52	4.94	1.08	1.34	1.04	7	6.96108
19	0.32	6.89	0.82	1.14	0.79	8	7.74618
20	1.08	0.89	1.38	0.48	1.67	1	0.98693
21	1.72	0.78	1.10	0.45	1.33	1	0.97052
22	0.92	0.78	1.18	0.61	3.44	2	1.55308
5	0.94	0.95	1.04	0.71	3.10	2	1.99460
16	0.90	0.98	1.10	0.72	2.78	2	2.01141

Tab.2: Comparison of the results from ANNs and Subjective Assessment

4. Conclusions

The approach developed provides an effective means for objective evaluation of PSQ. In comparison with other approaches, the method is capable of handling non-linear relationships between multiple parameters and subjective assessment results, and it can be used for on-line test. In addition, the approach provides a method to combine ES with ANNS in a co-ordinate fashion. In this way, a fuzzy AI system can be easily built. The bottleneck problems ů- acquisition of expert knowledge of ES and the ANNs training of BP ANNS have been solved in this application area.

References

[1] Mahar T.J., Postle R.: International fabric Handle Survey, proceedings, The Second Australia-Japan Symposium on Objective Measurement, Victoria, Australia, 1983, pp. 227–232

[2] Pan N. and K.C.Yen, Physical Interpretation of Curve Obtained Through the Fabric Extraction Process for Handle Measurement, Textile Research Journal, 1992, Vol. 62 (5), pp. 279–290

[3] Alexander K.T.W. Stosic R.G.: A New Non-destructive Leather Softness Test, Journal of the Society of Leather Technologists and Chemists, 1993, Vol. 77 (4), pp.139–141

[4] Leung Y.C., Yip D.H.F., Yu W.W.H.: An Analogue ANNS for Classification of Alcohol, Man, proceedings, 1997 IEEE International Conference on Systems and Cybernetics, vol. 1–5, pp. 790–795

[5] Behery H.M.: Comparison of Fabric Handle Assessment in the United States and Japan, Textile Research Journal, No. 5, 1986, pp. 227–236

[6] Guy R.: Laboratory Report, Part 1 and Part 2, British Leather Centre, Northampton, UK, 1977

[7] Yin H., Kong L.: Study on the new methods of fabric handle, Textile Journal 1993, Vol. 14 (2), pp. 543–548 (in Chinese)

[8] Yen K.C., Pan N.: The patterns Recognition Methods of Fabric Handle, Textile Journal, 1984, Vol. 5, pp. 731–739

[9] Pan N., Yen K.C.: A New Approach to the Objective Evaluation of Fabric Handle from Mechanical Properties, Textile Research journal, No. 3, 1992, pp. 438–445

[10] Kreuzer W., McKenzie B.: Programming for Artificial Intelligence, Addison-Wesley Publishing Company, Inc. Sydney 1991, pp. 2–11

[11] Lippman R.P.: An Introduction to Computing with Neural Nets, IEEE ASSS Magazine, 1987, 4, pp. 4–18

[12] Zhang J., Li R.: The structure and Algorithm of Neural Networks Expert System for On-line Control, Pattern Recognition & Artificial Intelligence, 1995, Vol. 8 (2), pp. 171–176 (in Chinese)

[13] Su Z.: Study on the On-line Test of Leather Handle with Artificial Intelligence, Doctoral Thesis, Sichuan Union University, P. R. China. Jan. 1996, pp. 76–89 (in Chinese)

Hybridní systém z expertního systému a neuronové sítě pro objektivní hodnocení smyslových vlastností výrobku

Subjektivní kvalita některých produktů, takových jako zpracování tkaniny a kůže, vůně voňavkářského zboží, chuť nápojů a jídla, jsou hlavně vyhodnocovány osobním pocitem a zkušeností. V tomto příspěvku je tento druh vlastností definován jako smyslové vlastnosti výrobků (PSQ).

Tradiční metody vyhodnocování PSQ jsou smyslové, používající k popisu osobního smyslového vnímání přídavných jmen jako „dobrý“, „špatný“ atd. Ale výsledky subjektivního vyhodnocování jsou fuzzy a nemůže jich být užito k řízení sebe sama. Vzhledem k rozdílu v kulturnímu zázemí a estetickým představám, existuje nízká shoda mezi těmi, kteří těchto přídavných jmen používají.

V literatuře byly navrženy shlukové metody v rozpoznávání vzorů, metody expertních systémů (ES) a umělých neuronových sítí (ANN) pro zachycení nelineárních vztahů mezi subjektivními výsledky a parametry zkoušky. Ale potíže při výběru charakteristik shluku, získávání znalosti pro výstavbu expertního systému a tréninku ANN nebyly dosud vyřešeny.

Jako řešení je v článku prezentován hybridní systém pracující jako expertní systém založený na neuronových sítích pro on-line testování PSQ. Expertního systému je použito pro hrubou klasifikaci a řízení skupiny neuronových sítí, ANN jsou použity pro uložení fuzzy znalostí a fuzzy usuzování. Systém se skládá z pěti modulů: báze znalostí, inferenčního stroje, databáze, neuronové sítě a uživatelského rozhraní.

V systému se produkční pravidla určují z logických znalostí expertů po ohodnocení vzorků, což může být snadno vyjádřeno v symbolické formě s dostatečně jasným zápisem. Naproti tomu neuronové sítě ukládají fuzzy zkušenosti ohodnocovacího procesu, které jsou v mysli experta, ale jsou těžko vyjádřitelné slovy. Při subjektivním ohodnocení PSQ hraje logická znalost ve srovnání s fuzzy zkušeností jen malou úlohu. Navíc funkcí expertního systému je pouze hrubě klasifikovat vzorky do skupin, zatímco velké množství fuzzy znalostí je uloženo v souboru parametrů neuronových sítí. Tak je báze produkčních pravidel poměrně malá, takže systém je rychlý. V systému spolupracují ES a ANN, aby se navzájem kompenzovaly.

Pro ověření uvedeného přístupu byla provedena testovací studie. Získané výsledky naznačují, že existuje značná shoda mezi subjektivním ohodnocením experty a objektivním vyhodnocením systému, báze znalostí systému může být vytvořena efektivně a vyhodnocení PSQ tak může být provedeno on-line.