A NEURO-FUZZY CONTROL SYSTEM FOR INTELLIGENT SEWING MACHINES

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Abstract. A Neuro-fuzzy control model has been devised for the next generation of the so called "Intelligent Sewing Machines". The model incorporates discrimination of material characteristics to be stitched by automatic determination of their properties. The fabric/machine interactions at different speeds have been computed in the form of linguistic rules of a fuzzy model and implemented in a neural network to allow for optimisation of fuzzy membership functions and subsequently, self-learning. The model is succesfully applied to an instrumented industrial sewing machine.

Introduction

Limp materials such as fabrics have to be stitched in order to form the shape of a 3 dimensional body, as in a garment. Sewing by a needle and thread has survived for centuries and this is the only means of joining acceptable to consumers. Fabrics are very complex materials for defining, they have different properties that interact with each other and change with processing. Sewing machines have inherent problems in the engineering sense also, through their complex mechanisms necessary for the many different stitch types. Optimisation of the conditions of sewing machines has been and still is one of the most important requirements for the textile, garment and retailing industries, and for the sewing machinery manufacturing industry. The complex interactions at the fabric machine interface has been the theme of study for some years, Stylios (1) and (2), the scientific deliverables of which have formed the foundations for research into the next generation of the so called "Intelligent Sewing Machines" that this paper is concerned with.

Problems Associated with Joining "Limp Materials". Although there is enough progress in relating fabric properties with sewing machine settings and stitching quality, there are still areas that cannot be numerically defined because they have not just one value of acceptability, but many values which can change all the time. In some circumstances properties interact with each other to produce a phenomenon - like a fault, in other instances they interact totally differently, producing a different fault or no fault at all. The behaviour is sometimes linear, especially for a limited sample of fabrics the majority of times it is vastly non-linear. These circumstances cannot all be effectively modelled. Seam quality itself can also have many definitions which are still subjective or even if measured have to retain the analogous subjective understanding; unbalanced stitch, without seam pucker, with no seam slippage, no holes, etc. Furthermore during the sewing machine operation a discrete problem may occur which cannot be modelled, such as pulling the fabric - inducing undue thread tension for instance. Solutions to all these problems have to be provided for effectively in the design of a new control model.

The Fabric/Machine Interface. From the results of an earlier study of the effect of fabric properties on the sewing process (2), Stylios et al (3) and (4), found the following fabric properties to interact significantly with the sewing process:

- thickness
- compression
- bending
- tensile
- friction

These properties can automatically be measured using specially developed measurement systems. An industrial sewing machine has been instrumented with sensors so that the following data can be captured at different sewing speeds:

- Sewing machine speed (measured by shaft encoder)
- Thread tension (diaphragm type strain gauge)
- Tension disk pressure (strain gauge)
- Presser foot pressure (strain gauge)
- Feed dog pressure (strain gauge)
- Feed dog differential (linear variable differential transformer)

A representative sample of commercial fabrics were selected, and 69 experiments were conducted on each fabric at different sewing speeds. To establish the effect of thread tension and foot pressure on seam quality, more than 1000 designed experiments in total

'Intelligent Systems Engineering', 5–9 September 1994, Conference Publication No. 395, © IEE, 1994

took place. Analysis of these results (4) established the theoretical sewing model and the rules for optimal control of the sewing machine (Table 1).

It has been revealed that sewing machine speed affects the static settings of the mechanisms which have an optimum of a particular fabric for an acceptable and consistent seam quality.

- Seam quality is reduced with increase of sewing thread tension.
- There is a relationship between presser foot pressure and sewing thread tension, seam quality is reduced with high foot pressure and high thread tension, whilst seam quality improves with increasing foot pressure and low thread tension.
- Generally speaking seam quality is reduced with increasing sewing machine speed and it further being reduced with increasing thread tension.
- There is an interesting trend for some fabrics to reach poor seam quality at speeds of around 3,500 rpm, and others to reach high seam quality at presser foot pressure of around 28N.

Neuro-Fuzzy Control Model

The building blocks of Fuzzy rules consist of linguistic expressions of the form

$$\textit{If } x \textit{ is } \tilde{A}, \textit{ THEN } y \textit{ is } \tilde{B} \textit{ ELSE } y \textit{ is } C$$
$$\textit{where } C \textit{ is the universe of discourse}$$

Relational rules of the form :

$\tilde{R} = (\tilde{A}\times\tilde{B}) \cup (\bar{\tilde{A}}\times\tilde{C})$ are then composed from the specified matrix operations.

Fuzzy logic linguistic control rules of the form:

IF _Fabric_ is poor **AND** _speed_ is high **THEN** _tension_ is low

can be used effectively when human operators can express the control knowledge that they use in controlling a process in terms of rules of the above form.

The linguistic rules determined from experimental data for the optimal control of the Pfaff 563 single needle industrial lockstitch sewing machine are shown in Table 1.

The fuzzy system control algorithm takes two inputs namely, sewing machine speed and fabric sewability, and maps them unto the optimum values of disc and foot pressures.

TABLE 1 - Fuzzy Associative Memories for Machine

FUZZY ASSOCIATIVE MEMORIES		Speed of Sewing Machine		
Optimised Parameter	Fabric Sewability	Low	Medium	High
Optimum Foot Pressure	Poor	Rule 1 **High**	Rule 2 **High/Med**	Rule 3 **Med**
	Average	Rule 4 **Low**	Rule 5 **Low**	Rule 6 **Low**
	Good	Rule 7 **Low**	Rule 8 **Low/Med**	Rule 9 **Med**
Optimum Disc Pressure	Poor	Rule 1 **Low**	Rule 2 **Low**	Rule 3 **Low**
	Average	Rule 4 **Med**	Rule 5 **Low**	Rule 6 **Low**
	Good	Rule 7 **High**	Rule 8 **Med**	Rule 9 **Low**

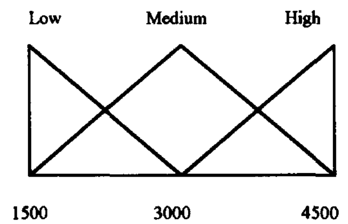

Figure 1 : Membership functions of Machine Speed

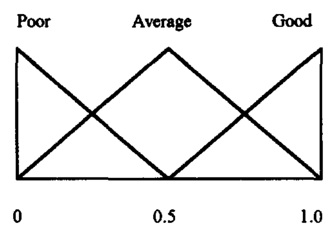

Figure 2 : Membership functions of Fabric Sewability

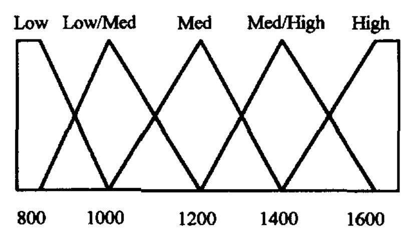

Figure 3 : Membership functions of Foot Pressure

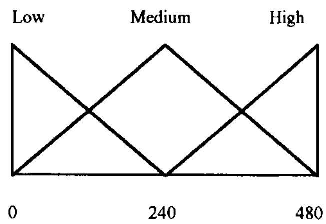

Figure 4 : Membership functions of Disc Pressure

While Neural Networks can be extremely well trained on numerical data once that the output is known, non-numerical knowledge and understanding of experts about the general trend and rate of change of variables' values cannot be easily incorporated (as it is with fuzzy logic). Therefore, it appeared that the synergy between Neural Networks and Fuzzy Logic was needed to enable automatic learning by a Fuzzy system.

The sewability of any given fabric was pre-determined prior to input into the fuzzy system. This pre-processing was performed by a neuron and a weight on each link between the neuron and a fabric property, trained using error back propagation, to accurately predict fabric sewability from its relevant physico-mechanical properties.

Furthermore, the learning capabilities of a neural network was used to optimise the input and output membership functions of the fuzzy system by implementing the system in a neural network.

●**Antecedents.** The antecedents layer of the neuro-fuzzy network consist of neurons which compute fuzzy membership functions (according to the expression below) for their outputs.

$$\mu_R(x,y)=\max\left[\left(\mu_{\tilde{A}}(x)\wedge\mu_{\tilde{B}}(y),\left(1-\mu_{\tilde{A}}(x)\wedge\mu_{\tilde{c}}(y)\right)\right)\right]$$

●**Rules (Aggregation of Relational Rules)** The rules layer consist of neurons which perform the composition and aggregation of fuzzy relational rules according to the following equations.

$$R = R^1 \cap R^2 \cap \ldots\ldots.. R^n \quad \textit{for conjunctive set of rules } (AND)$$
$$m_y(y) = Min[\mu y_1(y), \mu y_2(y), \ldots, \mu y_n(y)] \quad y \in Y$$
$$R = R^1 \cup R^2 \cup \ldots\ldots.. R^n \quad \textit{for disjunctive set of rules } (OR)$$
$$m_y(y) = Max[\mu y_1(y), \mu y_2(y), \ldots, \mu y_n(y)] \quad y \in Y$$

●**Consequence (Max-Min Method).** The neurons in the consequence layer determine the output of each rule by the equation below, Jamshidi et al (5).

$$\mu_y(y) = Max_k\,\{Max\{Min[\mu x_1(x_1), \mu x_2(x_2), \ldots \ldots \mu x_n(x_n), \mu_{Rn}(x_1, x_2, \ldots x_n, y)]\}\} \quad x \in X$$

over k number of rules.

Fuzzification of inputs was carried out at the inputs layer while deffuzification was performed at the outputs layer.

Triangular membership functions may be described by three parameters namely, the centre, left and right spreads. In the case of gaussian functions, the curvature is an additional parameter.

By replacing the standard sigmoid function

$$f(z) = (1+e^{-z})^{-1}$$

employed in forward propagation of Neural Networks by a function that incorporates these parameters in a network which implements the fuzzy system, automatic tuning was enabled, Berenji and Khedhar (6).

$\mu(x) = (1-|(x-c)/s|\ )$ for triangular functions

where c is the centre of the membership function, s is s_L for left spread or s_R for right spread and x is a value of the output variable.

For this application, all the input membership functions were left unchanged and automatic tuning was performed on output membership functions only (Figures 1 to 4).

The output layer performs the defuzzification of the fuzzy outputs. Table 1 shows the rules applied to the system and Figure 5 shows a schematic outline of the Neuro-fuzzy Network. Using Neuro-fuzzy, each layer of the neural network represents a step in the fuzzy logic procedure, for automatic tuning of its membership functions and a robust system.

The input layer consists of automatic determination of machine speed and fabric quality for a good seam. Fabric quality is determined by pre-processing fabric properties using a neuron having weights on the connections between the properties and the neuron.

The membership functions representing low optimum outputs were the most severely affected by the tuning, in terms of magnitude of change, and the direction of tuning i.e. they were reduced. The remaining tuned membership functions were marginally increased in size (Figures 6 and 7).

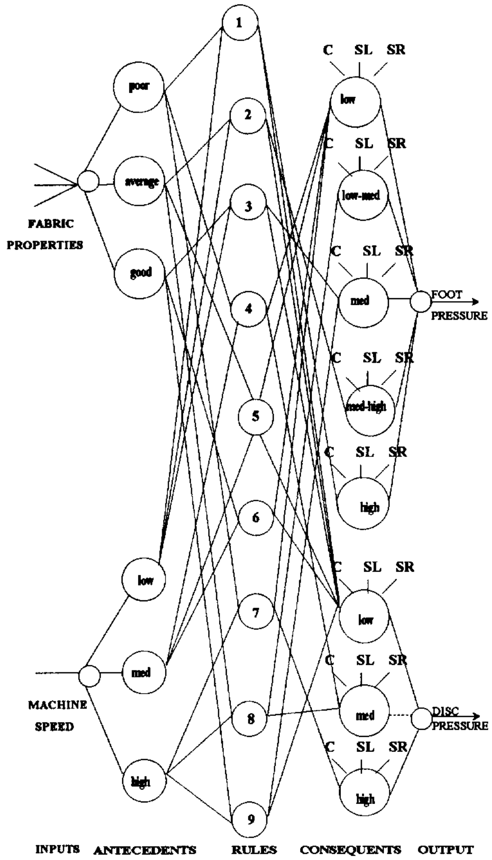

Figure 5: Neural Network Model of the Fuzzy System

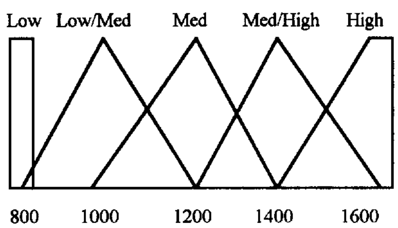

Figure 6: Tuned membership functions of foot Pressure

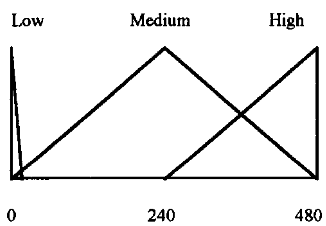

Figure 7: Tuned membership functions of Disc Pressure

Implementation and Validation

The three-dimensional control surfaces in Figures 8 and 9 show optimum pressures that correspond to all combinations of values of the two input state variables, fabric sewability and speed of sewing machine. Table 2 shows the measured properties of a sample of ten fabrics and the classification of their stitching qualities SQ on a conventional industrial sewing machine, one optimised by experts SQ (Ind), and another, controlled by the neuro-fuzzy system SQ (N-F).

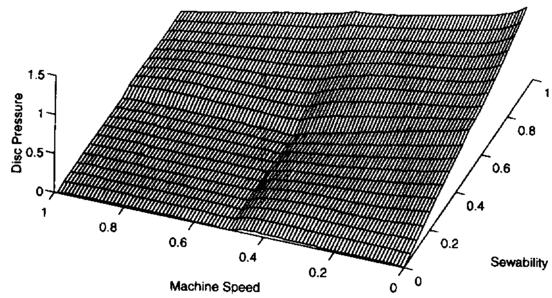

Figure 8: Control Surface of the Foot Pressure

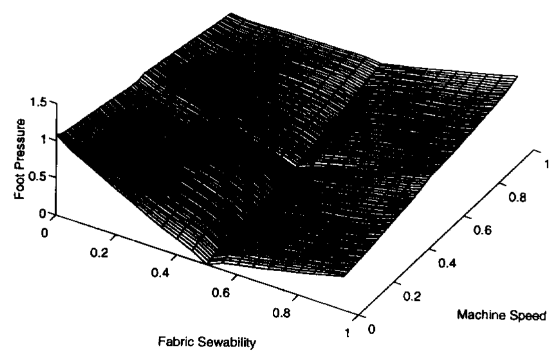

Figure 9: Control Surface of the Disc Pressure

Figure 10 : The Intelligent Sewing System implemented on an Industrial Lockstitch Machine

The range of classification for stitching quality is 1 to 5, 5 being the best, 1 is worst, and C denotes marginally worse quality than specified grade. The stitching quality results show that the values of the SQ (N-F) are generally higher than those of the corresponding SQ (Ind), suggesting that the performance of the neuro-fuzzy system is superior.

TABLE 2 - Properties and seam qualities of 10 fabrics.

Fabric	Wt. (gm/ m^2)	Thick (m)	Wp.FR (gm .cm)	Wf FR (gm .cm)	S. Q. (Ind.)	S. Q. (N-F.)
1	132	0.192	146.7	50.47	5C	5
2	118	0.168	93.34	60.44	3C	4C
3	102	0.142	55.96	57.77	3	5
4	141	0.244	44.33	107.6	5	5
5	103	0.124	73.90	26.85	3	4
6	117	0.194	29.11	52.08	3	5C
7	143	0.250	30.43	125.0	5	5
8	143	0.275	19.43	37.28	5	5
9	118	0.205	47.32	64.47	4C	5C
10	111	0.144	27.01	44.41	3	4C

Wt - Weight of fabric
Thick - Fabric thickness
Wp FR - Warp flexural rigidity
Wf FR - Weft flexural rigidity

Figure 10 shows the instrumented sewing machine with the motor acting on presser foot pressure for regulating the feeding of the material, and the motor acting on the sewing thread pressure for ensuring optimum thread tension. The interfaces with the computer and the representation of the real time optimum settings as bars on the computer screen are also shown.

Discussion and Conclusion

The synergism from a combined neural network and fuzzy logic approach has been found most successful for modelling the control of sewing machinery for complex interactions with limp materials. It is now possible to optimise sewing machinery settings automatically, statically and dynamically, for any textile material to be stitched. This research establishes the next generation of intelligent sewing machines in the developing area of intelligent Textile and Garment Manufacturing Systems.

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