A CONNECTIONIST EXPERT SYSTEM APPROACH FOR REPRESENTING A PRESS OPERATOR'S MACHINE-SPECIFIC KNOWLEDGE

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Abstract: An integrated connectionist expert system was developed to replicate the on-line inking adjustments that a press operator applies during a job run. The inking adjustments correspond to a mapping of the density deviations (between a sampled print and the match-print) to the ink key adjustments applied in order to overcome this deviation. The nature of a proficient operator's knowledge is machine-specific, i.e. he has learned to predict that particular machine's reactions, as observed on the print, to his compensatory control actions, consisting of the inking adjustments. The learning capabilities of connectionist networks (or neural networks) were integrated with the knowledge-based representation of a rule-based expert system in order to represent this machine-specific knowledge.

1. Introduction

During a job run, the press operator manipulates the amount of ink dispensed to the prints by altering the settings of the ink keys. The operator bases these on-line modifications on the observed deviations in print quality between the sampled prints and the match-print. The relationship between the amount of ink dispensed and the observed deviations was studied in this research. It was found that this relationship is machine-specific (Al-Mutawa, 1993). The operator's adjustments are

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highly dependent on his judgment and familiarity with the press that is being monitored. In other words, the operator is better able to predict the press outcome if he has worked on the same press over an extended period of time. Therefore, there exists a coupling of the operator's expertise with the particular press that is monitored.

In lithographic printing, the challenge in the derivation of a reliable mathematical model lies in the fact that the relationship of the process outputs to control actions is not constant from press to press (Al-Mutawa & Moon, 1993). Additionally, each press introduces unique characteristics. Sources of variability that characterize a particular press include its age, plate and cylinder wear, printing loads, and operating conditions, among others. A particular press may produce a significantly different quality print than another press with the same settings of the ink keys. Oftentimes, provisions are made in control systems which allow the operator to override the current commands in order to account for such machine-specific control actions.

Furthermore, the machine-specific relationship between the process outputs and the control actions may not be stable throughout a job run. During printing, the ink key settings that were established at the start of the job may not produce the same desirable print quality. These deviations are often attributed to process drift. For instance, the effect of the increased temperatures on the ink-handling cylinders alters the ink film thickness that coats the plate. Therefore, the ink key settings must be altered during a job run in order to restore the print quality. Even the settings obtained from ink-presetting systems often must be "fitted to the characteristics of individual printing presses by [the] know-how of a skilled operator" (Kobayashi, 1986).

It is customary in print shops for an operator to be assigned to work on the same press. This allows the operator to become familiar with the behavior of that particular press. The shortage of skilled labor exists in the printing industry not unlike many other trades (Business Indicator Report, 1992). Therefore, the unexpected loss of a skilled operator may have devastating effects on a print shop since a new operator must be trained to work on a particular press. The goal of this research is to develop a representation that can capture and preserve the machine-specific knowledge of a proficient press operator. A connectionist expert system representation was developed. The eventual aim of this representation is to contribute towards the preservation of valuable expertise and make this type of knowledge available to a novice.

This paper begins by introducing the properties of connectionist networks and expert systems. The developed system makes use of the properties of both representations in order to represent the machine-specific knowledge of a press operator. Then the stages in the development of the connectionist expert system are presented by describing the individual components that comprise the system. Finally, the paper concludes by a presentation of the research findings and a discussion of the results.

2. The Approach

The implementation of an integrated system combines the use of both a connectionist architecture and a rule-based expert system representation (Caudill, 1990; Gallant, 1993). These two representations possess complementary properties. Therefore, the resulting system has the properties of expert systems and connectionist networks without necessarily eliminating either one.

2.1 Properties of Connectionist Networks

A connectionist network (also known as neural network) is a collection of simple processing units linked by weight-carrying connections. A processing unit receives one or more signals along its input paths and sends one signal along an output path. These units are analogous to a biological neuron in the sense that each input has a relative strength or weight which corresponds to the synaptic strength of neural connections. In general, each processing unit propagates the weighted sum of the input signals. The output signal is produced as a result of modifying the inputs by means of a sigmoidal transfer function. Since many units can process computations simultaneously, connectionist networks are said to be inherently parallel.

Processing units are connected to each other by weighted connections where each weight corresponds to the strength of the connection. A positive weight represents an excitatory input and a negative weight represents an inhibitory input. The pattern of connectivity of the processing units determines the state, or knowledge content, of a network at any point in time. This pattern is described by the weights of the connections between the units at that instance. Connectionist networks are often utilized in applications where the relationship between inputs and outputs is unknown and data representing these stimuli are readily available.

A multilayer feedforward pattern of connectivity was found to exhibit a large measure of success for implementing input-output mappings (Rumelhart et al., 1986). A multilayer network is one where the units are organized in layers as shown in Figure 1. The number of input and output units in a network is primarily dependent upon the ultimate purpose of the system and the nature of the available data.

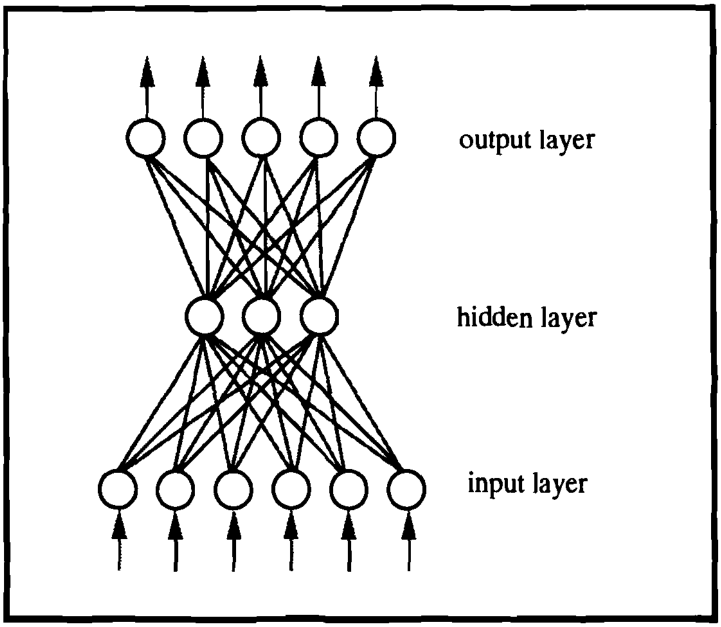


Figure 1 Interconnected Multilayer Network

Once the connectivity of the network has been established, the connection weights must be determined. The resolution of these weights constitutes connectionist learning. Learning is accomplished by a modification of the connection weights in response to input signals presented to the processing units. In order to reproduce the actions of a human expert, the set of weights that enables a network to produce outputs comparable to the responses of a human must be found. This is achieved through the implementation of learning rules.

2.2 Properties of Expert Systems

An expert system consists of a knowledge base and an inference engine. The knowledge base of an expert system is analogous to the long-term memory of facts, structures, and rules that comprise the domain-specific information of a human expert. A rule is represented in the form: *if* antecedent, *then* consequent. The antecedent of the rule is a set of conditions which must be satisfied for the rule to be proved. The consequent is the set of actions to be executed when the rule is proven. The knowledge is structured and codified in such a way that it can be manipulated by the inference engine (Parsaye & Chignell, 1988).

The inference engine is the mechanism by which rules are managed in the knowledge base of an expert system. The consequent actions of a rule may lead to the creation of new knowledge and/or the deletion of existing knowledge. It is the inference process that is responsible for the execution of the rules. Inference is cyclical and is made up of pattern matching, conflict resolution, and execution.

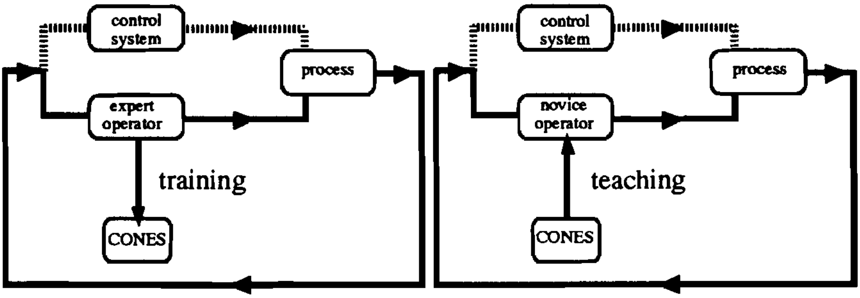
A data-driven inference strategy is applied in this research. This strategy is known as forward chaining. The available knowledge is used to deduce new knowledge and, therefore, producing a modified situation which eventually leads to the deduction of the goal. The matching phase of forward chaining identifies the set of rules in which the antecedent matches the existing knowledge. These rules are known as the conflict set and they are placed on the agenda. The conflict resolution phase is used to select a rule from the agenda for execution. The action phase involves the actual execution of one or more rules selected during the conflict resolution phase.

3. System Development

The system developed was named CONES (an acronym for CONnectionist Expert System). As a programming environment, CONES is designed to capture the expertise of an individual operator working on a particular press. CONES operates in two modes: Expert Mode and Novice Mode.

In Expert Mode CONES is *trained* by following the on-line corrective control actions taken by the experienced operator to restore the print quality. These actions are available to the programming environment as sets of corresponding observable and adjustable variables. It is the operator's conceptualization of the relationship between these sets of variables that the programming environment seeks to capture. A trained CONES is used in Novice Mode to provide expert recommendations to a novice for the particular press for which connectionist training was completed.

Figure 2 illustrates the flow of information for each mode. It should be noted that the presence of a control system does not interfere with the function of CONES since its purpose is not to replace the control system, but to replicate the on-line control actions performed by an operator who may be overriding the control system.



Expert Mode Novice Mode

Figure 2 Flow of Information

A connectionist representation is used to capture the unarticulated conceptualization of an experienced operator from process data. This representation is integrated with a rule-based expert system that utilizes forward chaining inference to model the process. Each component is described in the following subsections.

3.1 Connectionist Component

In past research, experimental connectionist networks have been trained by observing the actions of a human teacher (Mozer, 1987; Guez & Selinsky, 1988; Tesauro, 1989). Problem representation in these connectionist networks is often motivated by the desire to reproduce the kinds of coding principles that might be employed by the human teacher. Hence, the inputs to the networks in CONES represent the observable variables, namely the densities of the match-print and sample, and the outputs to the networks represent the adjustable variables, namely the ink key settings.

There are as many networks as the number of relations between dependent sets of variables. Since each ink color is controlled independently of the others then four networks are used to represent each of the four colors in lithographic printing. Each network consists of three fully-interconnected layers with: (1) four processing units in the input layer, (2) three processing units in the hidden layer, and (3) two processing units in the output layer.

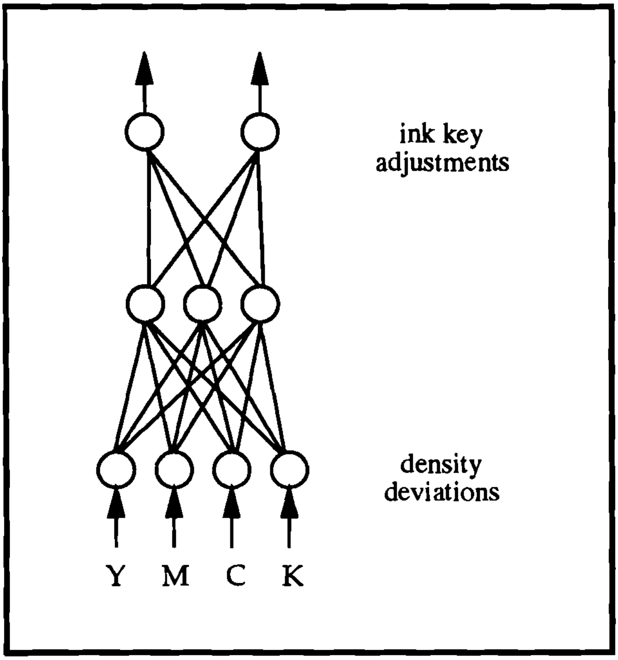


Figure 3 Network in CONES

The inputs to each network consist of the density deviations between the match-print and sample for the four ink colors in the same ink zone. The outputs of the networks symbolize a binary representation of the possible ink key adjustments based on the process data. The adjustments comprise the following four possibilities: (1) raise the ink key setting by 8–10%, (2) raise the ink key setting by 3–5%, (3) lower the ink key setting by 3–5%, and (4) lower the ink key setting by 8–10%. Figure 3 illustrates the structure of the connectionist networks.

The four connectionist networks in CONES are initially trained using backpropagation learning in Expert Mode. Backpropagation is a systematic method for training multilayer connectionist networks, it has strong and practical mathematical foundations. The development of the method is attributed to three independent research efforts (Werbos, 1974; Parker, 1982; Rumelhart et al., 1986). The objective of backpropagation training is to adjust the weights such that the application of a set of network inputs produces the desired set of outputs. Each input set is paired with a target output set, together these are known as a *training pair*.

During the training phase the desired, or target, outputs consist of the ink key settings applied by an experienced operator in response to the measured density deviations between the match-print and the newly sampled print. The goal of network training in Expert Mode is to find the connection weights that can produce network outputs such that the difference between the desired outputs and the network outputs is minimized. In other words, the weights are modified in order to reproduce the control actions of an experienced operator.

In backpropagation learning the introduction of a new set of training pairs to a previously trained network can erase or modify previous training by corrupting the weights, so complete retraining is necessary. However, specialized backpropagation learns incrementally. This means that the network weights can be updated as additional training pairs become available. Specialized backpropagation learning has been developed for adaptive control of closed loop systems (Psaltis et al., 1987; Elsley, 1988; Saerens & Soquet, 1989; Franklin, 1989). Therefore, specialized backpropagation is used for on-line training in Novice Mode. The specialized backpropagation learning model is implemented to incrementally train the networks in order to incorporate any changes in the relationships without obliterating previous training. Network training was implemented by means of NeuralWorks Professional II/Plus which is a connectionist network simulator.

3.2 Expert System Component

The expert system component of CONES was coded using the C Language Integrated Production System (Version 5.1). The initial fact base consists of: (1) the qualitative relations between the observable variables and their combinations and (2) the quantitative limits that the expert may impose on the variables for that particular application. The qualitative relations consist of: (1) the complementary relations between the subtractive primaries and (2) the combinatorial relations between the subtractive primaries. The quantitative limits imposed by an experienced press operator consist of the density limits for the particular press. The limits used in CONES correspond to the operator and the press from which the training set for the connectionist system was obtained.

There are three types of decisions to be made: (1) specification of the color of printing ink that requires adjustment, (2) determination of the direction of the alteration, and (3) determination of the amount of alteration. The outputs of the connectionist networks represent the amount of alteration for the adjustable variables based on the deviation between the current and desired observable variables. However, the decisions that determine which ink color should be adjusted and whether the amount of color needs to be augmented or reduced require additional knowledge of the qualitative relations between the observable variables and how specific alterations may affect the overall adjustment process. Therefore, the expert system embodies these qualitative relations in the form of rules.

The design of the rule base closely follows the decision-making process of an experienced operator. In general, the operator assesses the observations in a two-step manner. The first step corresponds to an individual assessment of the variables. In other words, the recommended adjustments are determined irrespective of their effect on the other variables. For example, in a particular ink zone the cyan ink key may be required to be raised by 10% and the magenta ink key is to be raised by 10% in order to make the sky bluer in that image area, and hence, restore the print quality. Suppose that in the same ink zone there were no deviations observed for the remaining inks, namely yellow and black, and their values did not exceed the range for the press. Therefore, an individual assessment of the yellow and black inks suggests that no adjustment is necessary to compensate for drift in these two colors since none has been recorded.

The second step in the decision-making process corresponds to a consideration of the individual assessments of the overall result. Using the previous example to illustrate this point, raising both the cyan and magenta inks affects their overlap with each other in addition to the overlap formed with the third subtractive ink color, namely yellow. In other words, the desired effect of intensifying the blue color of the sky can additionally intensify the cyan component of the green color and also intensify the magenta component of the red color in the same image area. This effect is undesirable because if it were required then an observation of the deviation in the red and green would have been detected. Therefore, the correct adjustment must be made without producing undesirable side-effects.

The second decision-making step determines whether any corrective actions are required to compensate for the effects of the individual adjustments and, if so, the nature of these adjustments. For the previous example, the yellow ink key may also be raised in order match the increases in the overlaps it makes with the cyan and magenta inks, and hence, restore the intensity of the green and red overlaps. However, this rise in yellow also causes the overall grayness of the image area to rise and this effect must be eliminated in order to restore the required print quality. Therefore, the black ink key is additionally reduced to compensate for the rise in the grayness of the image area.

The rule base of the expert system contains rules that replicate the described decision-making process. The rule base is divided into rule sets where each set is comprised of several rules. There are the preparatory rules, the comparison rules, the shift rules, the first-step rules, the second-step rules, and the cessation rules. These rules are triggered by forward chaining inference. The expert system is designed such that rules from the same rule set are placed on the agenda at any point in time. This leads to a greater modularity of the rule base.

The connectionist representation is integrated with the expert system by means of a conflict resolution technique that utilizes the connection weights. The execution of the expert system rules is governed by the level of importance assigned to each rule by means of the connectionist representation. The developed technique achieves the goal of integrating the operator's unarticulated conceptualization as represented by the connectionist system with the articulated representation in the knowledge base. Furthermore, as the experienced operator's conceptualization varies then an incremental learning procedure, i.e. specialized backpropagation, is implemented to update the connection weights subsequent to the initial training.

4. Results and Conclusions

Following network training, the weights of the connections between the input layer and the hidden layer were examined. These connection weights are shown in Tables 1, 2, 3, and 4. The four input units correspond to the density deviations for yellow, magenta, cyan, and black, respectively. The representation of inputs in all four networks are identical.

	hidden 1	hidden 2	hidden 3
input 1	3.718	13.688	25.808
input 2	1.701	-2.807	2.150
input 3	86.291	-7.423	7.845
input 4	1.228	-30.029	-7.140

Table 1 Connection Weights for Cyan Network

	hidden 1	hidden 2	hidden 3
input 1	-1.204	3.445	-47.110
input 2	52.428	36.553	-67.956
input 3	-6.901	7.653	-40.890
input 4	-4.022	4.472	-45.776

Table 2 Connection Weights for Magenta Network

	hidden 1	hidden 2	hidden 3
input 1	-21.538	16.398	98.595
input 2	-46.185	9.930	-4.901
input 3	-49.606	25.915	3.819
input 4	-9.720	7.038	-11.298

Table 3 Connection Weights for Yellow Network

	hidden 1	hidden 2	hidden 3
input 1	0.311	-0.236	0.118
input 2	-0.569	1.581	4.332
input 3	-4.374	0.998	1.855
input 4	-42.104	-42.226	-36.040

Table 4 Connection Weights for Black Network

The signs of the weights between the input layer and the hidden layer indicate whether the connection is excitatory or inhibitory. In other words, the input to a hidden unit that has formed a positive connection contributes to an increase in activation of the unit (i.e. excite), whereas a negative connection causes a decrease in activation (i.e. inhibit). An examination of the signs reveals that the connections between the input unit of the color to be adjusted in the particular network forms positive or negative connections depending on the hidden unit as shown in Table 5. For instance, the input unit that represents density deviations in yellow has formed a negative connection with the first hidden unit (–21.538), and positive connections with the second and third hidden units (16.398 and 98.595, respectively) in the network where the outputs represent adjustments in the ink keys for yellow.

Hidden Units	1	2	3
yellow input in yellow network	—	+	+
magenta input in magenta network	+	+	—
cyan input in cyan network	+	—	+
black input in black network	—	—	—

Table 5 Signs of Weights

The interesting finding is that the relation between the subtractive primaries of the ink colors and the additive primaries has been uncovered by the hidden units of the networks. According to color theory, each ink color filters out its complementary additive primary from white light and reflects the other two. Hence, yellow absorbs the blue component of white light while reflecting the green and red components. By designating the three hidden units as blue, red, and green, respectively, the negative connection formed with the yellow input coincides with the absorbed component, whereas, the positive connections are associated with the reflected components. The same designation applies to the other three networks. Moreover, all of the connections formed between the input that represents deviations in black ink were negative. This is consistent with the fact that black absorbs all of the components of white light.

In theory, each subtractive primary should fully absorb its complementary additive primary and fully reflect the other two additive components. Therefore, the connection between the density deviation of a particular color should inhibit the hidden unit representing the complementary additive and excite the hidden units that represent the other two additive components to the same extent. However, an examination of the magnitudes of the weights reveals that this is not the case in the connectionist networks. In fact, the networks capture the relationship between the non-ideal subtractive primaries of printing inks and the additive primaries in the magnitudes of the weights between the input and the hidden layers. Thereby, replicating the experienced operator's conceptualization of the quantitative balance between the proportions of inks based on their non-ideal behavior.

A conflict resolution strategy that makes use of the relationships between the observable and adjustable variables established by the connectionist networks has been developed for the expert system component in CONES. The weights between the input layer and the hidden layer were found to be an indicator for the current relationship between the observable variables and their combinations.

The conflict resolution technique developed in this research was named weight-based conflict resolution. During conflict resolution, the rules in the conflict set become associated with a salience value that corresponds to the relevant weights in the connectionist networks. The salience value explicitly sets a priority level to the rule. By prioritizing the rules in this manner, the rule with the highest salience value in a conflict set is executed. Therefore, the adaptiveness of the connectionist system to the current situation is reflected in the execution of the rules in the expert system. This allows the expert system to represent the current state of the process by way of the connectionist weights.

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