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A Survey of Neural Network Research and Fielded Applications

David H. Kemsley
Electronics Engineering Technology Department

Tony R. Martinez
Douglas M. Campbell
Computer Science Department,

Brigham Young University, Provo, UT 84602

Abstract

This paper gives a tabular presentation of approximately one hundred current neural network applications at different levels of maturity, from research to fielded products. The goal of this paper is not to be exhaustive, but to give a sampling overview demonstrating the diversity and amount of current application effort in different areas. The paper should aid both researchers and implementors to understand the diverse and potential impact of neural networks in real world applications. Tabular information is given regarding different features of neural network application efforts including model used, types of input and output data, accuracy, and research status. An extended bibliography allows a mechanism for further study into promising areas.

1.0 Introduction

This document summarizes promising neural network research and fielded neural network products in table format. Although not an exhaustive work, we give a broad overview of current neural network applications. The goal is to give a flavor of the breadth of application areas currently being targeted by neural networks, coupled with a non-exhaustive, but broad bibliographical guide to information on specific applications research.

Also of perhaps more importance to neural network researchers is an effort to tabulate

a) the type of neural network models being used,
b) *the form of both input and output data for the applications*, and
c) a rough measure of the accuracy of the systems for the particular applications.

Though no effort is here made to be exhaustive, we have strived to give a *broad* summary of applications research. A few representative applications from different areas have been arbitrarily chosen, classified, and summarized. Theoretical and model research is not discussed here since our focus is on working applications.

Every effort has been made to insure the integrity of the summarized data, but mistakes are inevitable due to the amount of data. The data is taken directly from published literature. When the published data is insufficient, we have left the corresponding table cells blank.

2.0 Neural Network Parameters

Seven parameters are used to summarize the selected neural network applications.

1. ***Application Type***. Eight broad areas are reviewed: Vision, Speech, Signal Analysis, Robotics, Expert Systems, Computers, Process Planning / Control, and Miscellaneous.
2. ***Application Description***. A descriptive title for each application.
3. ***Network Model***. The type and size of neural network(when available). This includes the following abbreviations- **BP:** Back-propagation, **CPN:** Counter-propagation network, **RCE**: Restricted Coulomb Energy, **Own:** Network designed specifically for the application, **Hybrid:** Either a mixture of networks or networks combined with other technologies, and **CMAC:** Cerebellar Model Arithmetic Computer

4. ***Input Data***. The data type (video input, digitizer tablet, grids, waveforms, etc.) and encoding technique (filtered, Fourier transformed, ranges of values, etc.).
5. ***Output Data***. The data type, number, and categories of classifications.
6. ***Accuracy / Results***. This includes the frequency of errors after training and comparison of neural network accuracy and speed with conventional processing techniques. Where possible, we include the number of training examples required to achieve various performance levels.
7. ***Project Status***. We give (1) the simulation size, (2) the simulation scope, (3) whether the project is hardware or software, and (4) whether the project is research or a fielded product. Project status is encoded using the following symbols- **T**:Theory, **P**: Proposal, **F**: Fielded Product, **S**: Small scale simulations (simulations for proof of concept, simulations with small amounts of training data, and simulations with few output classifications), and **L**: Large(r) scale simulations or hardware implementation. These symbols are sometimes combined when the application is a combination of the above classifications or marked by (?) when the proper classification is unclear.

References (shown in the last column) give the primary author's name in italics. The sponsoring organization is also included in ordinary font when space is available. The primary author's name is sufficient to locate the bibliographic reference.

We begin each of the eight categories with an explanation of the criteria for classifying applications in that section. We give some background information and certain applications (referenced in the text with SMALL CAPITOL letters and marked in the table with an asterisk.) In addition, this preliminary text explains some of the more difficult table entries.

3.0 Fielded Products and Promising Research

3.1 Vision

Character Recognition: The first section of the table looks at character recognition applications. The Nestor Learning System™ is at the heart of many fielded applications in character recognition. Their HANDWRITTEN CHARACTER RECOGNITION application claims to recognize approximately 2,500 Japanese Kanji characters with 92% accuracy. Their HANDWRITTEN DATA ENTRY application uses a digitizer tablet to enter handwritten data into a computer. Their ZIP CODE RECOGNITION application claims to recognize handwritten ZIP codes with 97.7% accuracy in the system's maximum accuracy mode. Their SIGNATURE VERIFICATION application claims to verify signatures written on any type of check with a "4% rate of false alarms" compared to "50% false alarm rates for humans."

Other: The SILICON RETINA is a 48 x 48 pixel silicon retina chip which "generates, in real time, outputs that correspond directly to signals observed in the corresponding levels of biological retinas [adaptive intensity sensitivity, time response, response to edges and Mach band response]."

Application Description	Net	Input Data	Output Data	Accuracy / Results	Stat-us	Reference
Character Recognition	Neo-cog-ni-tron	Various handwritten Arabic numerals on a 19x19 Grid	1 of 10 numerals	Able to recognize distorted numerals	L	*Fukushima* NHK
Handwritten Character Recognition*	RCE	2,500 individual characters		Kanji & Hiragana: 92% Katakana: 95%	F	DARPA 517 Nestor literature
Isolated Word Recognition	Wis-ard	Multiple digital encodings	voting output units for specific words	90-100% range	S	*Badii*
Handwritten Data Entry*	RCE	Uses digitizer tablet	Data entered directly into computer		F	Nestor
Character Recognition	Featu re maps 32x 32	32x32 pixel image	Character classification Eliminates noise	Good results for small training set	S	*Allinson* Univ. of York UK
Signature Verification*	RCE	Signatures on any check background	Valid / Forged signature	4% false alarms	F	Nestor

ZIP Code Recognition*	RCE	7,200 training, 1,800 test numerals		97.7%	F	Nestor
AC Coupled Retina with Cooperative Receptors		Visual image	Adaptive contrast sensitivity, adaption resolution		S	DARPA 469, 507 SAIC
Silicon Retina*	own	Visual image on 48x48 VLSI pixel array designed for automatic gain control	Adaptive sensitivity, edge detection		L	*Mead* CalTech
DETE: Learning Visual / Verbal Associations	own	2-D 'visual' field, English sentences describing this image			P/S	*Nenov* UCLA
Face Recognition	BP	32x32 grid, 256 gray scale images	1 of 4 faces		S	*Midorikawa* Seikei Univ.
Image Compression	BP	2x2 to 8x8 grids			S	*Cottrell* UC San Diego
Shape Categorizer	own	Numerals, Characters, Electronic Symbols	Category	94-98%	S	*Kirshman*

3.2 Speech

Speech Recognition: The ELECTRONIC COCHLEA uses VLSI technology to "convert time-domain information into spatially encoded information by spreading out signals in space according to their time scale." Since each of its 480 stages has an exponentially increasing delay time, "faster sequences [in time] create output patterns closer to the input of the structure; slower sequences generate output patterns nearer to the output of the structure." This silicon cochlea "exhibits behaviors that bear an uncanny resemblance to those of the living systems."

The PHONETIC TYPEWRITER is a continuous speech recognition system used as a keyboard aid for computer data entry. Raw speech waveforms are preprocessed (filtered, digitized, Fourier transformed, log spectralized) on an IBM AT compatible with two digital signal processors and fed into a single layer of 8 x 12 self-organizing processing units each of which represent a single (or sometimes duplicated) speech phoneme. Each spoken word traces a unique path through these units (the sequential phonemes of the word.) A subsequent grammar algorithm pieces together individual words. Six male voices were used to train this system for one hundred of the most common office words. The system was between 92% and 97% accurate in unlimited text transcription mode depending on the speaker and text difficulties. The system's accuracy was between 96% and 98% for a possible 1000 words. Each word requires about 250 ms processing time.

The WORD RECOGNIZER is an Intel 8086 microprocessor based system which has been used on auto assembly lines since 1982. Vocal data is entered into a data collection system within 0.5 seconds of the utterance at 99% accuracy (trainer's voice) with an active vocabulary of 50 out of 200 total words.

Speech Synthesis: The NETTALK: TEXT TO SPEECH CONVERSION system is a well known text to speech conversion network. The back-propagation network's input consists of seven groups of processing elements, each encoding possible letters or special symbols in a word or sentence. The output nodes produce the proper phoneme (for the DECtalk speech synthesizer) for the middle input symbol of a seven symbol window. The other six symbols provide context for the middle symbol. A network with no hidden units was 82% accurate when taught one thousand of the most common English words. With 120 hidden units this accuracy increased to 98%.

Application Description	Net	Input Data	Output Data	Accuracy / Results	Stat-us	Reference
Electronic Cochlea*	own	Time domain waveforms into a 480-stage VLSI delay line	Spatial representations of the input	biologically plausible	L	*Mead* Cal Tech
Phonetic Typewriter*	Ko-ho-nen	Finnish and Japanese voice waveforms	Words entered into computer as aid to the keyboard, 250 ms / word	92-97% in unlimited text tran-scription mode	L/F?	*Kohonen* Helsinki University of Technology

Speaker Recognition (2 Speakers)	BP 16x8 x8	10 ms windows of continuous time- amplitude speech waveforms	1 of 2 speakers	80%+	L	*Castelaz* Hughes
Word Recognizer (in use since 1982)*		Spectral voice data	200 word vocabulary, 50 active at a time	99% recog. of trainer's voice w/i 0.5 sec.	F	DARPA 417, 524 Marcian E. Hoff, Jr.
Hiertalker: Learning to Read Aloud	Hierarchic Correlation Net	Word strings 6219 training examples	Proper phonemes for DECtalk speech synthesizer	99% training set, 76-96% other	L	*An* Los Alamos Natl. Lab
Attaching Scenes to actions	own	simple action statements	properly correlated scenes/sequences	good empirical results	S	*Sharkey* Univ. of Exeter, UK
NETtalk: Text to Speech Conversion*	BP	1000 of most common words, scrolled through a 7 letter window	Proper phoneme (for middle letter in window) for DECtalk speech synthesizer	82%	L	*Sejnowski* Johns Hopkins University

3.3 Signal Analysis

Signal Analysis: Signal analysis is one of the largest neural network research areas. We include applications which analyze sensor data, usually obtained as a reflected signal. *Signal Recognition and Classification* applications classify a target by the received signal, while *Target Tracking* applications link together consecutive target 'snapshots.'

Signal analysis presents several problems. Real world signals vary in position, scale and rotation from the pattern a system is trained with. For example, a target recognition system may have been trained with an aircraft image viewed at 10°, but the working system may receive a signal from an angle of 45°. Matching the real image with a training image is computationally intensive. Most applications utilize preprocessed signals which are position, scale, and rotation invariant.

Computation time limits current signal analysis techniques. The more data a system must handle (e.g., an increase in image angles or targets) the longer the processing time required by conventional algorithms. Neural networks may solve computationally intensive problems due to their generalization capabilities and parallel processing techniques.

Signal Recognition and Classification: Many *Signal Recognition and Classification* applications transform a time domain signal into the frequency domain (usually by a Fourier transform) and use only the magnitude of the resulting information (phase is usually neglected.) Presently applications are limited to a few output classifications. Recognition accuracy ranges from 80 to 100% which is better than comparable algorithmic classification techniques.

Nestor's RADAR TARGET RECOGNITION application distinguishes radar target waveforms with 100% accuracy and clutter with 95% accuracy. An optimal Bayes classifier for the same data has 93% accuracy for targets and 90% accuracy for clutter.

Target Tracking: The TARGET TRACKING application merges consecutive 2-D "snapshots" of objects. Their neural network can track fifteen targets in about the same time as the same network requires to track two.

Application Description	Net	Input Data	Output Data	Accuracy / Results	Stat-us	Reference
Helicopter Recognition for Smart Weapons		Doppler radar data	1 of 8 helicopters		S/L	DARPA 570 TRW
Incoming Threat Assessment	BP 6x8x8		Launch command for interceptors	85-90%	S?	*Castelaz* Hughes

Infra-Red Target Classification	BP 2x2x 3; K-net	Infra-red data (Test: 10,000)	Two features, three classes	BP: 4.5% below theo-retical opti-mum K: 18.4% & 11.1%	S	DARPA 509 Night Vision Lab
Laser Target Recognition	BP 22x 200x 60x 4	Zernicke transformed laser radar data Train: 200, Test: 40		Equal to performance of standard nearest neighbor classifier	S	DARPA 511 Air Force Institute of Technology
Orca Call Recognition	Neu-ron Ring	Fourier transformed Orca call waveforms		80 to 100%	S/L	*Taber* General Dynamics
Laser Position, Scale and Rotation Invariant Target Recognition	BP	Laser radar data Fourier transformed with log radial and angle axis	1 of 2 Classes (in-class / out-of-class)	80-95%	S/L	*Troxel* Air Force Institute of Technology
Radar Target Classification	BP 16x 16x 16	32 synthesized radar exemplars Fourier transformed into 16 Frequency Bins (includes time)	1 of 4 munition types	92%+	S	*Castelaz* Hughes
Radar Target Recognition*	RCE	Radar targets and clutter data	Targets / clutter	RCE: 100% /95% Bayes: 93% / 90%	F	Nestor
Sonar Classifier		Power spectral envelope from rock and mine sonar data	1 of 2 (rock or mine)	Training: 99.8% Test: 90%	S	DARPA 421 Hughes
Target Tracking*		'Snapshots' of consec-utive 2-D images with multiple targets		Approx. same pro-cessing time for 2 & 15 targets	S	DARPA 477 TRW

3.4 Robotics

The **Robotics** table is divided into *Autonomous Vehicles* and *Manipulator Trajectory Control*. The *Autonomous Vehicles* section contains autonomous systems and subsystems. This grouping is somewhat arbitrary. *Manipulator Trajectory Control* applications provide control signals to robot manipulators. Robotics is a fertile field for neural networks due to neural networks' capacity to adapt, learn and generalize.

Autonomous Vehicles: We have classified six of these applications as large scale since they involve hardware and not merely software simulations. For example Fujitsu Laboratory's MOVEMENT CONTROL created ten autonomous robots (four wheels, two motors) which can interpret sensor data and make appropriate, simple decisions. Five capture robots were programmed to seek light and ultrasonic waves. Five escape robots were programmed to dislike light. This combination allowed the robots to act as 'cops and robbers.'

Boston University's VISUAL TRACKING AND NAVIGATION system uses two cameras on top of a 5-axis 'neck' to detect and track moving objects in real time using eye control techniques similar to the human visual system. When mounted atop a mobile robot, MAVIN (Mobile Adaptive Visual Navigator) will follow another object.

Application Description	Net	Input Data	Output Data	Accuracy / Results	Stat-us	Reference
Decision Making for an Autonomous Roving Vehicle		Sensor data, scientific goals, physical state	Recommended vehicle activities		L	*Eberlein* JPL

Visual Tracking and Navigation*	Adal-ine	Visual data	Camera movement control		L	*Waxman* Boston Univ.
Forklift Robot	C-MAC	Infra-red proximity de-tectors	X,Y,Z, roll, pitch, yaw control signals to retrieve pallet	7 training points to succeed	L	DARPA 445 Martin Marietta
Maze Learning		Current position in maze	Next step to come closer to goal		P/S	*Pinette* Univ. Mass.
Movement Control*	own	Visual, ultrasonic and tactile sensors	Control of robot direc-tion	10 robots played 'cops and robbers'	L	*Nagata* Fujitsu Laboratories
Pursuit Fleeing	TIN	Visual data	Next desirable position		S	*Winter*
Robot Navigation	Hop-field	Ultrasonic sensors	'World map' of environment with obstacles, path planning	"Demonstra-tion unit is operational"	L	DARPA 540 Thompson CSF-pro
Spacecraft Attitude Determination by Star Pattern Recognition		Simulated star field	Current three-axis internal orientation		S	*Alvelda* JPL

Manipulator Trajectory Control: A robot's kinematics are complex, making the design of an algorithm for robot manipulator control difficult and time consuming. Furthermore, theoretical manipulator kinematics do not accurately represent the robot's actual kinematics. The algorithms that exist to solve this problem are not practical for real time control [Josin]. If the manipulator is bent or if the robot's orientation is changed from the programmed position by collision or vibration, then the algorithm must be revised. Obstacle avoidance is difficult to program since obstacle position is often dynamic. Neural network adaptability and generalization capabilities help alleviate these problems.

Graf and LaLonde's COLLISION FREE MANIPULATOR MOVEMENT system autonomously learns robot kinematics, workspace constraints, hand-eye coordination, collision avoidance, and kinematic and sensor changes.

Josin, Charney and White's POSITION CORRECTION experiments use a conventional manipulator controller to produce uncorrected joint angles for a robot whose structure has been changed by either having its base or a distal link bent. A back-propagation network produces joint angle corrections which are summed with the controller's uncorrected output to produce the final joint angles. After training on a single point the accuracy of the resulting endpoint improved 60% over using only the uncorrected joint angles. Training on eight points improved the accuracy eleven fold.

Application Description	Net	Input Data	Output Data	Accuracy / Results	Stat-us	Reference
Collision Free Manipulator Movement*	Hy-brid	Obstacle, arm, and camera data	Movement control?		P/S	*Graf: IEEE* *Graf: INNS*
Position Correction*	BP	Desired manipulator endpoint from con-troller, uncorrected joint angles	Joint angle corrections	1100% im-provement with 8 train-ing points	S	*Josin* Neural Systems Incorporated
Topology Conserving Maps for Motor Control	Ko-ho-nen	Joint angle sensors	Brief torque pulses		S	*Ritter* Technical Univ. Munich
Intelligent Control of Intelledex 605T Robot Manipulator	BP	Manipulator angular position, desired posi-tion	Limb control signals		S/L	*Sobajic* Case Western
Weld Seam Tracking	BP	Camera data	Welder control		S/L ?	*Xu*
Generic Robot Hand Controller Architecture	BP	Cylinder diameter and height	Grasp mode (power grasp, lateral pinch, pulp pinch, hook grip)		S	*Liu* USC, L. A.

Tactile Imagery (Analog Processing Chip)	Hop-field	Sensor data	Chip does mathematical inversion		P/S	*Pati*

3.5 Neural Expert Systems

An application is placed in the *Neural Expert Systems* section if the paper stated that the application was an expert system or if the application functioned as an expert system. Neural expert systems promise to learn complex relationships without requiring a Knowledge Engineer to undergo the time consuming task of rule formulation.

Medical Services: Both Hecht-Nielsen and Nestor produce systems which analyze EKG signals.

Saito's MEDICAL DIAGNOSTIC EXPERT SYSTEM diagnoses twenty-three different diseases (from 216 symptoms) with 67% accuracy after training on 300 examples. A comparable conventional expert system has 70% accuracy.

Application Description	Net	Input Data	Output Data	Accuracy / Results	Stat-us	Reference
DESKNET: A Dermatology Expert System	BP	18 symptoms, 200 training examples	1 of 10 papulosquamous skin diseases	70%+	S	*Yoon* Univ. Texas at Arlington
EKG Signal Classification	RCE	EKG signal	Normal or PVC heartbeat	100%	F	Nestor
EKG Signal Identification		EKG signal (window of last 40 samples, 200 μS long)	Reconstructed waveform with noise filtered out	Equal to a finite impulse response filter	F	DARPA 534 Hecht-Nielson
Lower Back Pain Diagnosis	BP	50 symptoms from multiple choice questionnaire; 100 training patterns	1 or 2 of 4 back pain types	77 to 80%	S	*Bounds*
Medical Diagnostic Expert System*	BP 216 x72 x23	216 symptoms from multiple choice questionnaire, 300 training patterns	23 different diseases	67% (70% from expert system)	L	*Saito* NTT
Tumor Recognition from Infra-Red Images	BP	Gray scale IR image of tumors	1 of 7 tumor stages		S	*Egbert*
Walking Aid for Paraplegics		Raw electromyographic data	"Functional Electrical Stimulation" for muscle control		P?	*Uth* Univ. Illinois at Chicago

Financial Services: Financial Services contains the largest number of fielded neural network products. Many address loan evaluation. Nestor's MORTGAGE ORIGINATION UNDERWRITER determines whether a mortgage loan application should be accepted or rejected based upon the applicant's financial status, the property data and other information. Several accuracy levels can be selected in this network. The network is 100% accurate when processing 30% of all applications presented (shown as "100% @ 30%" in the table). The network is 87% accurate when processing 100% of the applications (87% @ 100%). Nestor's MORTGAGE INSURANCE UNDERWRITER decides whether to insure a mortgage. Nestor's MORTGAGE DELINQUENCY UNDERWRITER predicts whether a loan will become delinquent; it claims to reduce delinquencies by 12%

Adaptive Decision System's LOAN UNDERWRITING system claims to increase profits by 18%.

The MARKET ANALYSIS network was trained on Yen currency trading data to identify "approximately 25 separate features [which] were... validated against available industry information." Later tests, asking novice traders to base their buy and sell decisions on the network's output, claimed "that even inexperienced traders could learn to make profitable decisions using information from the neural network."

Application Description	Net	Input Data	Output Data	Accuracy / Results	Stat-us	Reference
Bond Rating	BP	Company financial info, 47 companies	Bond Rating (AAA, AA, A, BBB, ...)	76 to 92%	S	*Dutta*

Loan Underwriting*	BP	Applicant information, 271,000 training examples	Estimated loss (percentage of dollars not repaid to outstanding funds)	18% profit increase	L/F ?	*Smith* Adaptive Decision Systems
Market Analysis*		Foreign currency trading data	Features of the data	see text	F	Hecht-Nielsen
Mortgage Origination Underwriter™ *	RCE	Personal financial profile, property risk factors, etc	Accept / Reject, confidence level, justification	100% @ 30%, 87% @ 100%	F	*Collins, E. &* Nestor Literature
Mortgage Insurance Underwriter™ *	RCE	Personal financial profile, property risk factors, etc	Accept / Reject ?, confidence level ?, justification	96% @ 30%, 82% @ 100%	F	Nestor
Mortgage Delinquency Risk Processor™ *	RCE	Personal financial profile, property risk factors, etc	Risk (Good / Bad)	70% @ 10%, 65% @ 33%, 12% reduction	F	*Ghosh &* Nestor Literature

Medical & Financial Services Data Encoding Techniques: Medical and financial applications, except for TUMOR RECOGNITION FROM INFRA-RED IMAGES and WALKING AID FOR PARAPLEGICS, usually use patient or applicant information derived from multiple choice questionnaires. Each input node represents an individual answer on the questionnaire.

Three encoding methods are used: Binary Values, Continuous Values, and Arbitrary Metrics. Binary values are used for simple statements about the existence of a characteristic such as “Do you have a headache?” as well as for answers to questions such as “How long has this symptom existed: (a) Day, (b) Week, (c) Month, ...” Continuous values are used to describe real quantities. Nestor uses a range of 0.0 to 1.0. Arbitrary metrics are used to encode data in a binary fashion.

3.6 Computer

This class of applications directly support or accomplish tasks done on conventional computing platforms. These include associative memory, text retrieval, sorting, intelligent interface, network routing, and paging support. Excaliburs' TEXT SEARCH AND RETRIEVAL allows searching of text files for given patterns where the queries or patterns may contain spelling errors.

Application Description	Net	Input Data	Output Data	Accuracy / Results	Stat-us	Reference
ANNA: Human / Computer Interface (learns user's habits)	BP?	History of environmental object use	Prediction of which object is most likely to be needed		S/L ?	*Jones* Arthur D. Little, Inc.
Content Addressable Memory		Binary Vector	Binary Vector		S	DARPA 575 Honeywell
Distributed associative memory for database design	DAM	Binary Vector	Binary Vector	Correct even though 20% Corruption in Network	P/S	*Char* Univ. Of Minnesota
Image Database		Keyword descriptors of image	Appropriate image		S/L	*Cochet* Univ. of Rennes
Adaptive Network Router	ASO CS	Binary Addresses	Binary Destination Address		T	*Mcdonald* BYU
Interface for Motor Impaired	Hop-field	Joystick	Spatial organization of program choices		S/L ?	*Hohensee* Gould Inc.
Page Swapping Need Prediction	own	Current page number	Most & least likely pages to be needed		P?	*Lawson* Stetson Univ.
Sorting (A/D Conversion)	Hop-field	Analog values	Digital representation		S	*Gray*
Text Search and Retrieval	own	Ascii File/Pattern	Pattern Location		F	Excalibur

3.7 Process Planning / Process Control

The *Process Planning / Process Control* table includes applications that optimize a process or sequence of processes.

Global Holonetics' Smart Camera AUTOMATED INSPECTION SYSTEM is a hybrid system using counter-propagation and back-propagation networks, a RS170 video camera, "2-D optical Fourier feature extraction," and a Hecht-Nielsen ANZA board in IBM's PC-AT. It is able to sort or classify products passing in front of the camera.

Application Description	Net	Input Data	Output Data	Accuracy / Results	Stat-us	Reference
Automated Inspection System*	Hybrid CPN / BP	Visual data	Classified, sorted data		F	*Glover* Global Holonetics
Broom Balancer	Adaline	65 images on a 5x11 Grid: 5 cart positions, 13 pendulum angles	Direction of force	incorrect responses: 3.5%	S	*Tolat* Stanford Univ.
GTE Process Monitor	Adaline	Sensor data	Predicted yield and other data	'to be installed'	S/L ?	DARPA 411
Job Shop Scheduling	Hopfield	Available machines, jobs and sub-tasks to be executed	Near optimal production schedule		P/S	*Foo* Univ. South Carolina
Industrial Parts Inspection	RCE	Images of automatic transmission stators	Three types	97%	?	DARPA 516 Nestor
Nestor Development System™	RCE	Sensor data	Control signals	Improves on ES Methods	F	Nestor
Plan Reminding and Sequential Plan Manipulation	Hybrid	Goals, constraints, current status and context	Plan Sequence		P/S	*Veezhinathan*

3.8 Miscellaneous

Application Description	Net	Input Data	Output Data	Accuracy / Results	Stat-us	Reference
Predicting outcome of electrophilic aromatic substitution	BP 25x5 x2	Chemical info about 'first ring-substituent' (32 training, 13 test)	Orthoparadirecting substituent or meta-directing substituent		S	*Elrod* Upjohn Co.
Sequence Generation	BP	Incorrectly spelled name (inserted, deleted, substituted, & transposed letters)	Correct spelling		S	*Kukich* Bell Communications Research
Traffic Monitoring	Wisard 3 layer 2688 node	Digital 2 dimensional input image	Voting percentage of the 128 outputs for classifying between an automobile or taxi	Good results on training set fair for test set	S	*Goldstone* Imperial College, UK
Ship Layout Optimization	Hopfield	Environmental factors (ship noise, motion, vibration), associations between facilities			S/L	*Lee, W.* ChungNam National Univ.

4.0 Conclusion

This paper has given a sampler of current applications research in the neural network arena. Though no attempt to be exhaustive was made, the paper seeks to give a broad view of the diversity and extent of current neural network application areas, and to discuss types of input/output, accuracy, and status of the

research. The tabular scheme seeks to give a mechanism of easy reference and information to both researchers and potential users of neural networks.

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