

Can Face Recognition or LPR BENEFIT your company?

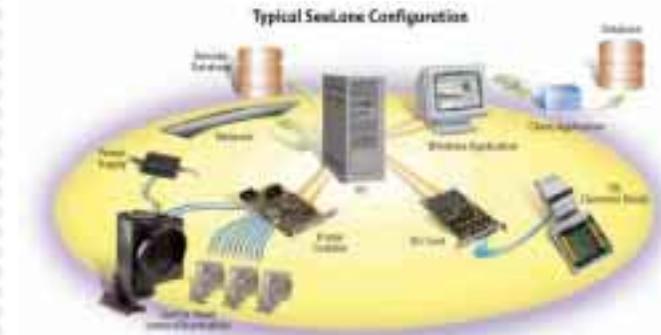


Barry Dudley (MBA (IT) & MSc (IA))
I-CUBE (Integrated, Intelligent Imaging)

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License Plate Recognition



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LPR use - 5 easy steps:



1 - Capture



3 - OCR



2 - Find plate



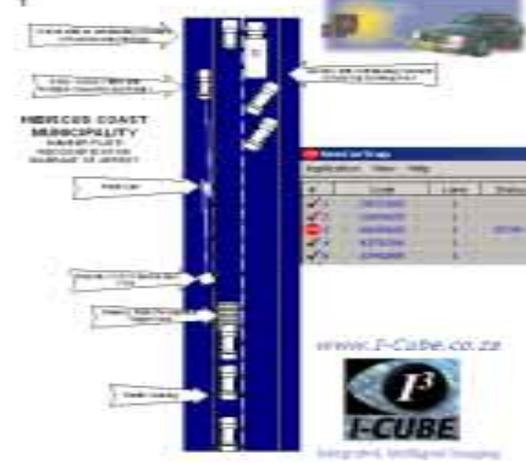
**4 - Alarm
Open gate**



5 - Report

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Portable LPR system (1/2)



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Face Recognition



Applications

- Biometric authentication for credit cards, passports, drivers licenses
- Time and attendance/business security
- Prison security
- Border monitoring
- Automatic identification for government agencies
- Home security
- Hotel and casino security
- E-Commerce
- ATM machines



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Face Recognition System





Analogue to digital converter
(Frame Grabber)



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Face Recognition - verification



Use face recognition to **assist in verification**, compare live image of the person against the saved facial images obtained when the person was enrolled.

One is using face recognition to **CONFIRM CLAIMED IDENTITY** (identity from a PIN, Card or other biometric).

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Face Recognition - identification



Use face recognition to **POSSIBLY IDENTIFY suspects**, compare the image of the person against the various WANTED databases. **RESULT** is a list of the closest matches to the person. Essential for an **operator to review the results**, making the decision.

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Face Recognition USE

- 1 - Load DataBase
- 2 - or OWN Images
- 3 - Compare
- 4 - Add new PERSON

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DataBase: Many databases exist:

- Local criminals
- Police
- Employees
- Male
- Female
- White
- Black
- Gambling
- Shoplifting
- Transport Workers
- Allowed on ship
- Not allowed to employ
- Etc.

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AND CORPORATION **Overview**

Introducing the exciting new field of **Biomimetic Intelligence.**

AND Corporation is the provider of Application Development Services, Software Systems and Licensor of this breakthrough technology.

The HNeT technology applies the power of digital holography within synthetic neuron cells. Assemblies comprised of such cells have one-to-one correspondence with the primary cell structures of the brain. These biomimetic structures provide the capability for truly real-time learning, and present a vast increase in (stimulus-response) memory storage capacity.

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AND CORPORATION **Overview**

Employing holographic principles, HNeT cells provide both real-time learning and dramatic improvements in performance over structurally more complex back-propagation / genetic neural networks.

The HNeT technology is not limited to face tracking / identification, but may be similarly applied to numerous areas within the medical sector, process control, automation, defence, financial, etc.

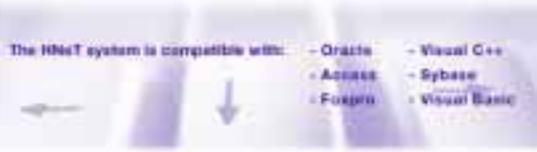
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HNeT Tools



| | | | | | | | | | |
|--|--|-------------------------|---------------------|-----------------------------|-----------------|----------|--------------|--|------------------|
| Operating Platforms | Windows 95, 98, NT and 2000 Limited UNIX versions available Custom features provided for multithreaded operation | | | | | | | | |
| Maximum # Cell Assemblies | 64,000 | | | | | | | | |
| Maximum # Input / Output Fields Per Cell | 16 Million | | | | | | | | |
| Operating Speed | > 40 Million Connections Per Second (CPS) on Pentium III processors | | | | | | | | |
| Cell Types Provided | <table border="0"> <tr> <td>Receptor</td> <td>Granule</td> </tr> <tr> <td>Stellate</td> <td>Pyramidal</td> </tr> <tr> <td>Purkinje</td> <td>Temporal</td> </tr> <tr> <td colspan="2">Signal routing (i.e. appending / extraction)</td> </tr> </table> | Receptor | Granule | Stellate | Pyramidal | Purkinje | Temporal | Signal routing (i.e. appending / extraction) | |
| Receptor | Granule | | | | | | | | |
| Stellate | Pyramidal | | | | | | | | |
| Purkinje | Temporal | | | | | | | | |
| Signal routing (i.e. appending / extraction) | | | | | | | | | |
| Cell Assembly Models | <table border="0"> <tr> <td>Supervised feed-forward</td> <td>Unsupervised</td> </tr> <tr> <td>Recurrent (hyperincurative)</td> <td>Spatio-temporal</td> </tr> <tr> <td>model</td> <td>Neo-cortical</td> </tr> <tr> <td></td> <td>Cerebellar model</td> </tr> </table> | Supervised feed-forward | Unsupervised | Recurrent (hyperincurative) | Spatio-temporal | model | Neo-cortical | | Cerebellar model |
| Supervised feed-forward | Unsupervised | | | | | | | | |
| Recurrent (hyperincurative) | Spatio-temporal | | | | | | | | |
| model | Neo-cortical | | | | | | | | |
| | Cerebellar model | | | | | | | | |

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The HNeT system is compatible with:

- Oracle
- Visual C++
- Access
- Sybase
- Foxpro
- Visual Basic



A particularly powerful aspect of the HNeT system is the facility provided for implementation and control of neural plasticity. Neural plasticity allows the HNeT system to optimize and reconfigure cell assembly structures in an automated manner. Neural plasticity guides the process of synaptic pruning and re-growth. This process automatically adapts and optimizes the neurological structure during stimulus-response learning, providing a dramatic improvement in accuracy and generalization.

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The HNeT2000 Application Development System is the software that runs the AcSys Biometrics Facial Recognition System.

Using only 3 Cerebellar assemblies, this program tracks up to 4 people in real-time and identifies each with 100% accuracy.




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Performance Features

Unique to the HNeT technology. The most basic cell assembly (based on the cerebellar model) is comprised of two synthetic neuron cells (granule and Purkinje).



| | |
|----------------------------|--|
| General Comparisons | Provides general performance characteristics pertaining to learning speed and accuracy, with comparisons to traditional neural networks |
| Convergence | Illustrates the learning convergence characteristics that occur when learning over multiple training exposures or epochs |
| Generalization | Concerns aspects concerning generalization and interpolation of the stimulus-response mapping |
| Neural Plasticity | Describes the process of neural pruning and regrowth, and illustrates performance gained through the resultant optimization of input combinatorics |

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General Comparisons



The holographic / quantum neural approach (HNeT) does not require a search process, and learns many orders of magnitude faster than traditional back-propagation or genetic based neural networks. **The Monte Carlo Test**

(Stimulus-response patterns comprised of random numbers, use 5 input variables for the stimulus and one response variable, with values uniformly distributed between 0.0 and 10.0).

- 1 - Stimulus-response memory capacity of the system,
 - 2 - Recall accuracy of the trained cell,
 - 3 - Learning speed.
- (Performance figures shown for a 160 MHz Pentium II.

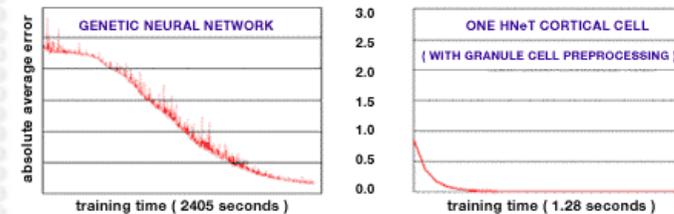
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Comparison 1 - Learning 100 Stimulus-Response Patterns



After the initial genetic search, training time applied to the genetic neural network is 40 minutes. By comparison, training time for the HNeT system is 1.28 seconds.

At a storage density of 100 patterns the HNeT granule-cortical cell structure is 100 times more accurate and 2000 times faster than the traditional neural network.

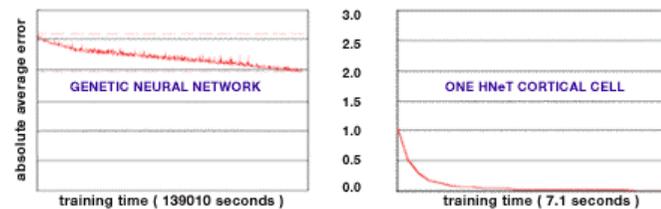


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Comparison 2 - Learning 500 Stimulus-Response Patterns



Increasing the number of stimulus-response patterns causes the genetic neural network to approach a state of saturation. At this level of storage density, traditional neural networks break down. Learning capacity of the HNeT granule-cortical cell combination is unaffected by the increase in storage, and displays a convergence similar to the prior test.

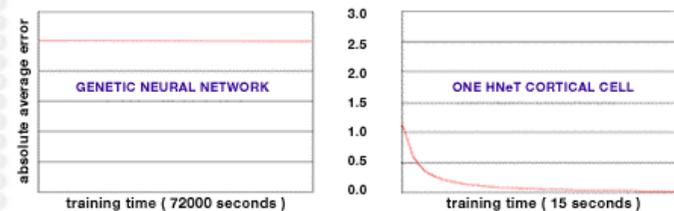


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Comparison 3 - Learning 1000 Stimulus-Response Patterns



At 1000 stimulus-response patterns the genetic neural network is unable to achieve any measurable level of convergence, even after 20 hours of training. The rapid learning characteristic of the HNeT system is again unaffected by this increase in storage density.



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The Mathematics



A stimulus-response pattern or "memory" may be represented by a set of values, reflecting conditions or states measured within an external environment, such as pressure, temperature, brightness, etc. During stimulus-response learning, neural cells associate or "map" one set of analog values (i.e. the stimulus fields) to an associated set of values (i.e. the responses). When the stimulus is distributed over a time span, one has spatio-temporal learning.

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The Mathematics for HNeT permits vast numbers of stimulus-response patterns to be learned and superimposed



(enfolded) onto a matrix comprised of complex scalars, called the cell's cortical memory. In fact, the number of values used to store cortical memory is often no larger than the number of values contained within a single stimulus pattern. The mechanism for holographic storage displays a capacity to achieve extremely high information densities, due to the fact that large numbers of stimulus-response memories can be enfolded onto the same set of scalars (in other words - computer RAM).

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**NEXT STEP –
Make an informed decision by trying
out the FULLY FUNCTIONAL
TEST SYSTEMS on the CD.**

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