Reference: Schomaker, L., Hoenkamp, E. & Mayberry, M. (1998). Towards collaborative agents for automatic on-line handwriting recognition. Proceedings of the Third European Workshop on Handwriting Analysis and Recognition, 14-15 July, 1998, London: The Institution of Electrical Engineers, Digest Number 1998/440, (ISSN 0963-3308), pp. 13/1-13/6.

Towards collaborative agents for automatic on-line handwriting recognition

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projects in the Cognitive Engineering group at NICI :

- On-line recognition approaches
- Comparison of forensic handwriting systems
- UNIPEN
- Multimodal speech and handwriting input
- Information Retrieval/Information Filtering
- Content-based image retrieval
- $\boxed{\text{Hybrid (NN/AI) modeling}}$

- **Multi-level information integration**
- **Agents: old for new?**
- **A triple-agent system**

"context"

- Use of context: a panacea for limited bottom-up classification performance?
- It is difficult to realize efficient use of context:
  - in case of complex input (cf. OCR of newspaper page vs. OCR of mail envelope)
  - under dynamic and free input conditions (writing a letter on a pen computer)

”context”

- What? (... are the relevant context bits: the ”frame” problem, Pylyshyn)
- How?
- No elegant solutions for multi-level information integration exist, as yet

syntax

- **Earlier experiments with NLP & on-line recognition: disappointing**
- **Parser for Dutch, using sentences from office context**
- **Batch architecture (strokes → characters → words → sentence)**
  - **use of context postponed until last word of sentence .**
  - **was slow!**
  - **written input may be syntactically incorrect**
  - **writers don't write job applications or love letters in this way**

syntax, continued

Needed: interactive approach
(e.g., incremental parser)

- **probabilistic language models**

  (works: but large corpus needed, many parameters)

- **grammars**

  (concise & explicit: but may lack information)

How to make a system which is modular and dynamically configurable?

old wine in new bottles?

- **O.G. Selfridge (1958)**

  Pandemonium: a paradigm for learning in mechanisation of thought processes. Proceedings of a Symposium Held at the National Physical Laboratory, pages 513–526, London, November 1958. HMSO.

- **Daemons**

- **Critics gallery**

- **Multiple experts**

- **Society of mind**

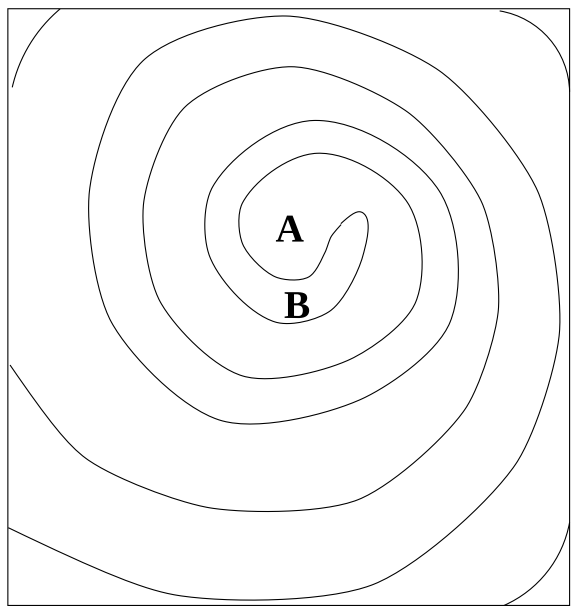
what's new?

- **Good definitions (Wooldridge & Jennings)**
- **Game theory, negotiation algorithms**
- **Multi-sensor fusion algorithms**
- **Learning**
  - **genetic algorithms**
  - **case-based reasoning**
- **Formalisms: Knowledge Interchange Format (KIF), Knowledge Query and Manipulation Language (KQML)**
- **Try:** `http://ontolingua.nici.kun.nl`

Potential for pattern recognition:

- **Realisation of complex decision boundaries**

again: the double spiral argument



- **Solve geometrically, e.g., with a MLP?**
  → Overfit!

- **Solve algorithmically, by search?**
  → More powerful!

experiment:

design a system

- **simple**
- **interactive (user is present & time is real)**
- **using bottom-up and top-down information**
- **using agent architecture**

→ **in order to see what the use of syntactic information may yield under simplified conditions**

design issues

- no natural language input but Scheme program input on a pen computer
- interactive:
  - no machine font substitution, leave ink 'as is'
  - use color for state feedback
  - give user full control, using virtual buttons, menus etc.
- bottom-up: Kohonen LVQ classifier of unistrokes
- top-down: Scheme parser (LR, incremental)

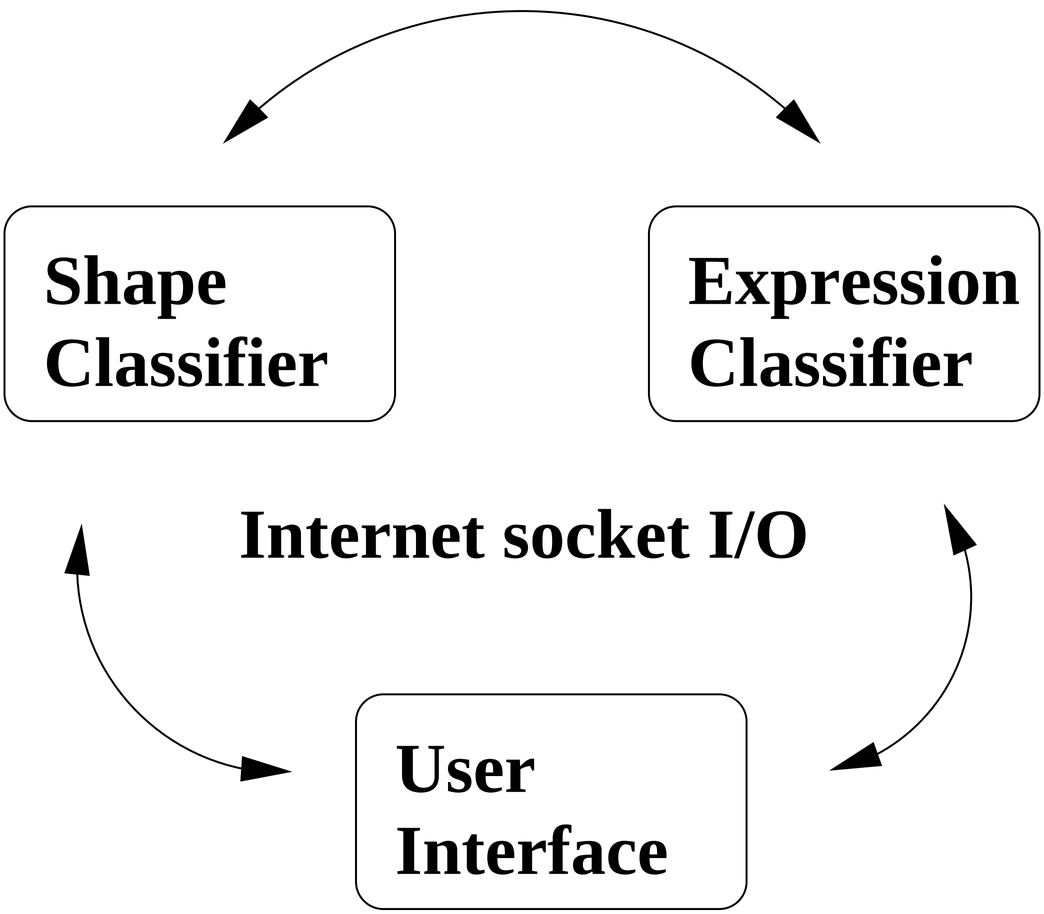
Scheme code example (towers of Hanoi)

```
hanoi.scm

(define ringlist
  (lambda (l n)
    (define mring
      (lambda (size)
        (cons 'ring size)))
    (if (= n 0)
        l
        (ringlist (cons (mring n) l) (- n 1)))))

(define mpole
  (lambda (ndisks)
    (cons 'pole (ringlist nil ndisks))))

(define disks
  (lambda (pole)
    (cdr pole)))
  .
  .
  .
  .
```

implementation

Agents:

1. shape classifier
2. expression classifier
3. user+user interface



Shape Classifier agent

- **Input: tokens of the Scheme language, written as unistrokes**
- **unistrokes, resampled to 60 samples**
- **Kohonen LVQ, nearest centroid match**
- **translate to** $\vec{\mu} = (0, 0)$
- **normalize rms radius to** $\sigma_r = 1$
- **feature vector:**
  - (x_k, y_k) **60 normalized coordinates**
  - $(cos(\phi_k), sin(\phi_k))$ **59 pairs**
  - **total 119x2=238**
- **training, 5-10 samples of a token**
- **learning rule** $f_j = \eta x_j + (1 - \eta) f_{j-1}$
- **token recognition rate** $\approx$ **85%**

Shape Classifier agent (pseudo code)

```
Init:
   init-communication
   read-table-with-token-templates
   ask-parser-for-type-of-each-token

while(true) {
   switch (read-request()) {
   case unistroke
      classify unistroke
      query-parser
      combine-parser-expectancy-and-shape-classification
      notify-user-agent

   case train
      update-token-shape-and-label
      notify-user-agent

      .
      .
   }
}
```

Expression Classifier for Scheme

- context-free grammar
- LR parser: incremental, no look ahead
- use lex/yacc (shift/reduce)
- tokens:

'	/
(	=
)	and
*	begin
+	BOOLEAN
-	case
.	CHAR
cond	let
define	let*
delay	NUMBER
do	or
else	set!
if	STRING
lambda	VAR

Expression Classifier for Scheme

- **Example of rule:**

```
state 29
        Def :  LPAR DEFINE_VAR Expr RPAR
        Def :  LPAR DEFINE_LPAR VAR RPAR Body RPAR
        Def :  LPAR DEFINE_LPAR VAR DefFormals RPAR Body RPAR

        VAR  shift 55
        LPAR  shift 56
        .  error
```

- **After each token: generate list of expected tokens and update state**

- **Requests to parser agent:**
  Accept_token
  Reset_state
  Delete_token
  Forward_token

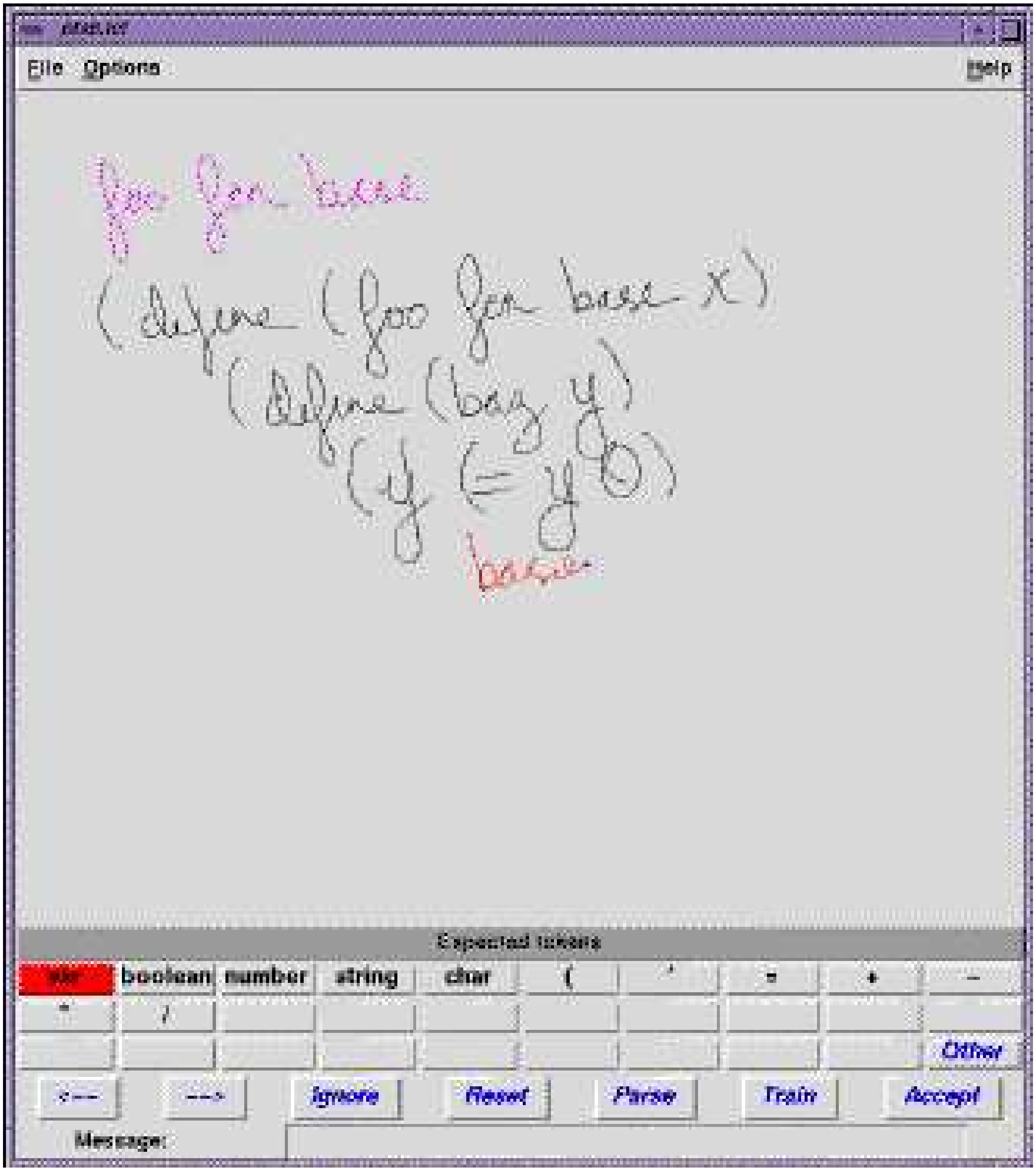
Expression Classifier agent (pseudo code)

```
Init:
   init-communication
   read-grammar

while(true) {
   switch (read-request()) {
   case token
       process-token
       update-parser-state
       return-expected-tokens

   case reset
       reset-parser-state
     .
     .
}
```

User Interface agent (pseudo code)

```
init-communication
start-parser
start-classifier

create-windows
create-event->task-bindings
      (ink events, parser events, classifier events)

wait-for-events(forever)
```

User Interface



interaction example

- **VAR expected**
- **token *dog* written**
- **token *dog* rejected → must be new token!**

results

good news:

- 100% 'recognition'
- users (Scheme programmers) like it!
- agent architecture is very convenient

results

bad news:

- individual information contributions by the agents must be analysed and quantified
- VAR becomes a problem in case of unconstrained scope
- NUMBER and STRING are open categories

results

Information content of Scheme source code

Symbols	$N_{alphabet}$	$^2log(N_{alphabet})$	*Entropy*	*Redundance*
Raw token stream	2003	11.0	6.3	4.7
Lumped token stream	28	4.8	2.4	2.4

(Based on corpus of N=27310 tokens.

Lumped means: use placeholders instead of actual instances of VAR.)

Entropy: $-\sum_{i=1}^{N_{alphabet}} p_i \, ^2log \, p_i$

results

Parser expectancy

Symbols	Avg. $N_{alternatives}$
Raw token stream (VAR scope=whole corpus)	1891.5
Raw token stream (VAR scope=single function)	97.4
Lumped token stream	16.0

(Scheme source-code corpus of 27310 tokens.

Lumped means: use placeholders instead of actual instances of VAR.)

→ If scope is not limited to a single function, the parser adds very little information. Reasons: users' naming creativity and the presence of constants (string, number).

- User actions are definitely needed!
- But their work can be made easier by using syntactical context
- The virtues of a grammar:
  "Look Ma' - No probabilities!"
- Beware of placeholders (name slots) in the grammar
- Just a first step towards the use of a multiple-agent architecture