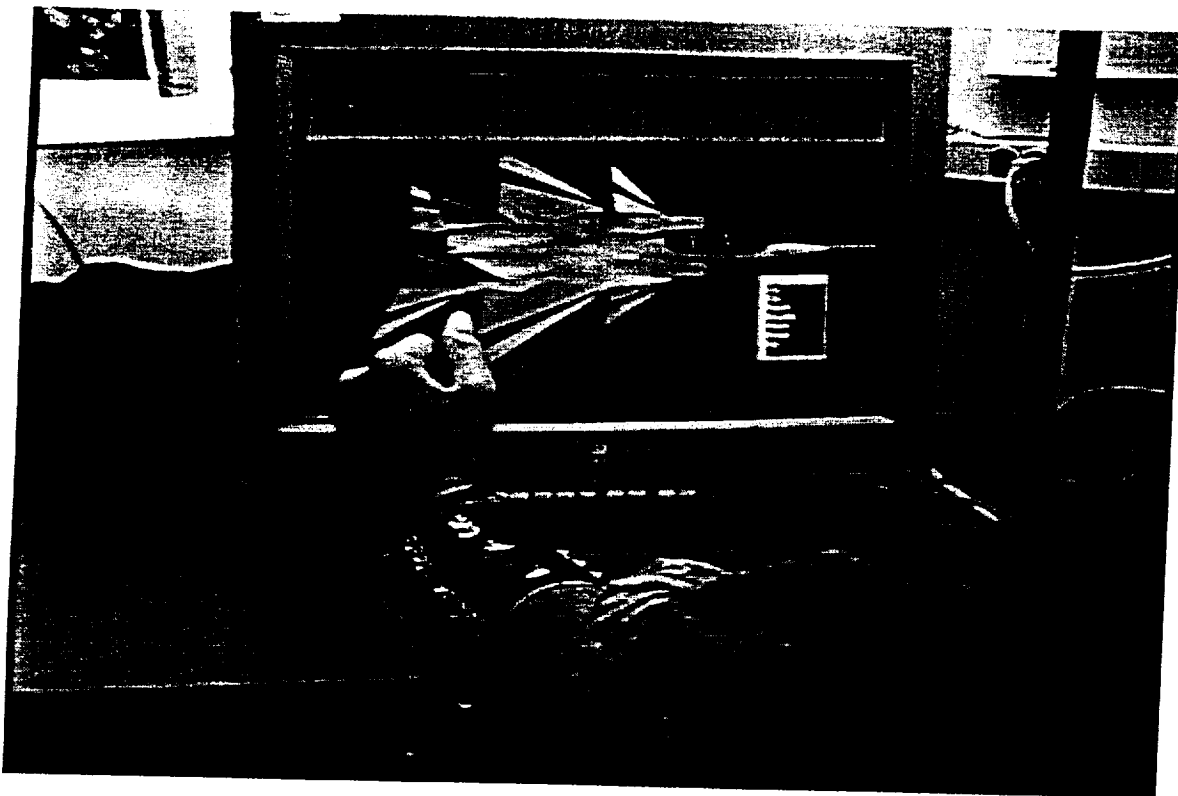


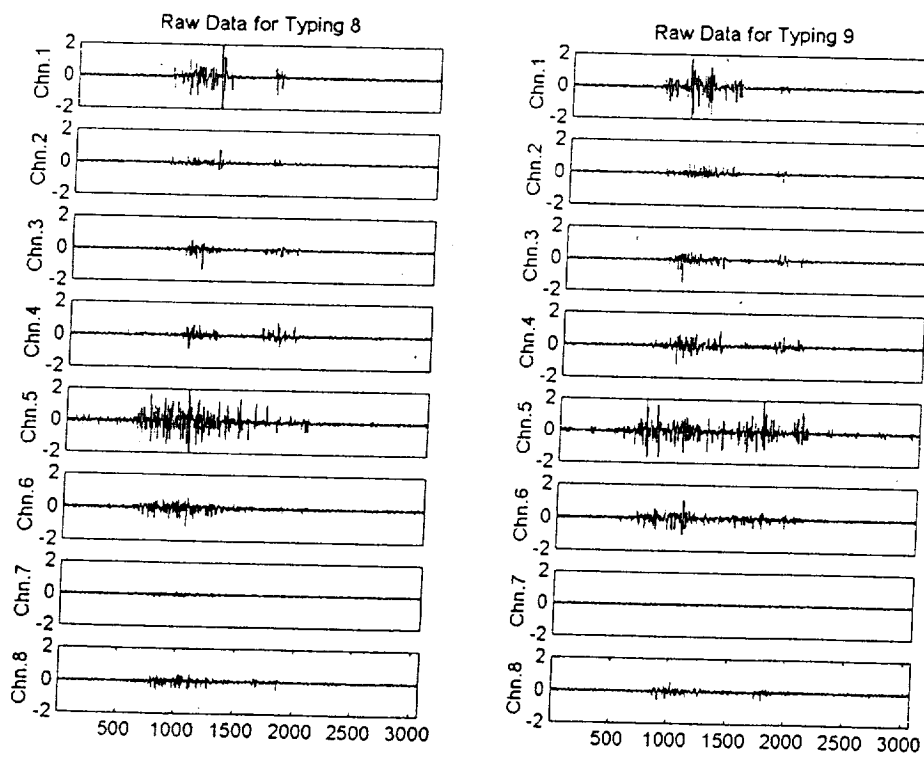
## Neuroelectric Virtual Devices

Kevin Wheeler, Computational Sciences Division, NASA Ames Research Center  
Charles Jorgensen, Computational Sciences Division, NASA Ames Research Center

This paper presents recent results in neuroelectric pattern recognition of electromyographic (EMG) signals used to control virtual computer input devices. The devices are designed to substitute for the functions of both a traditional joystick and keyboard entry method. We demonstrate recognition accuracy through neuroelectric control of a 757 class simulation aircraft landing at San Francisco International Airport using a virtual joystick as shown in Figure 1. This is accomplished by a pilot closing his fist in empty air and performing control movements that are captured by a dry electrode array on the arm which are then analyzed and routed through a flight director permitting full pilot outer loop control of the simulation. We then demonstrate finer grain motor pattern recognition through a virtual keyboard by having a typist tap his fingers on a typical desk in a touch typist position. The EMG signals are then translated to keyboard presses and displayed. The paper describes the bioelectric pattern recognition methodology common to both examples. Figure 2 depicts raw EMG data from typing the numeral '8' and the numeral '9'. These two gestures are very close in appearance and statistical properties yet are distinguishable by our hidden Markov model algorithms. Extensions of this work to NASA missions and robotic control are considered.



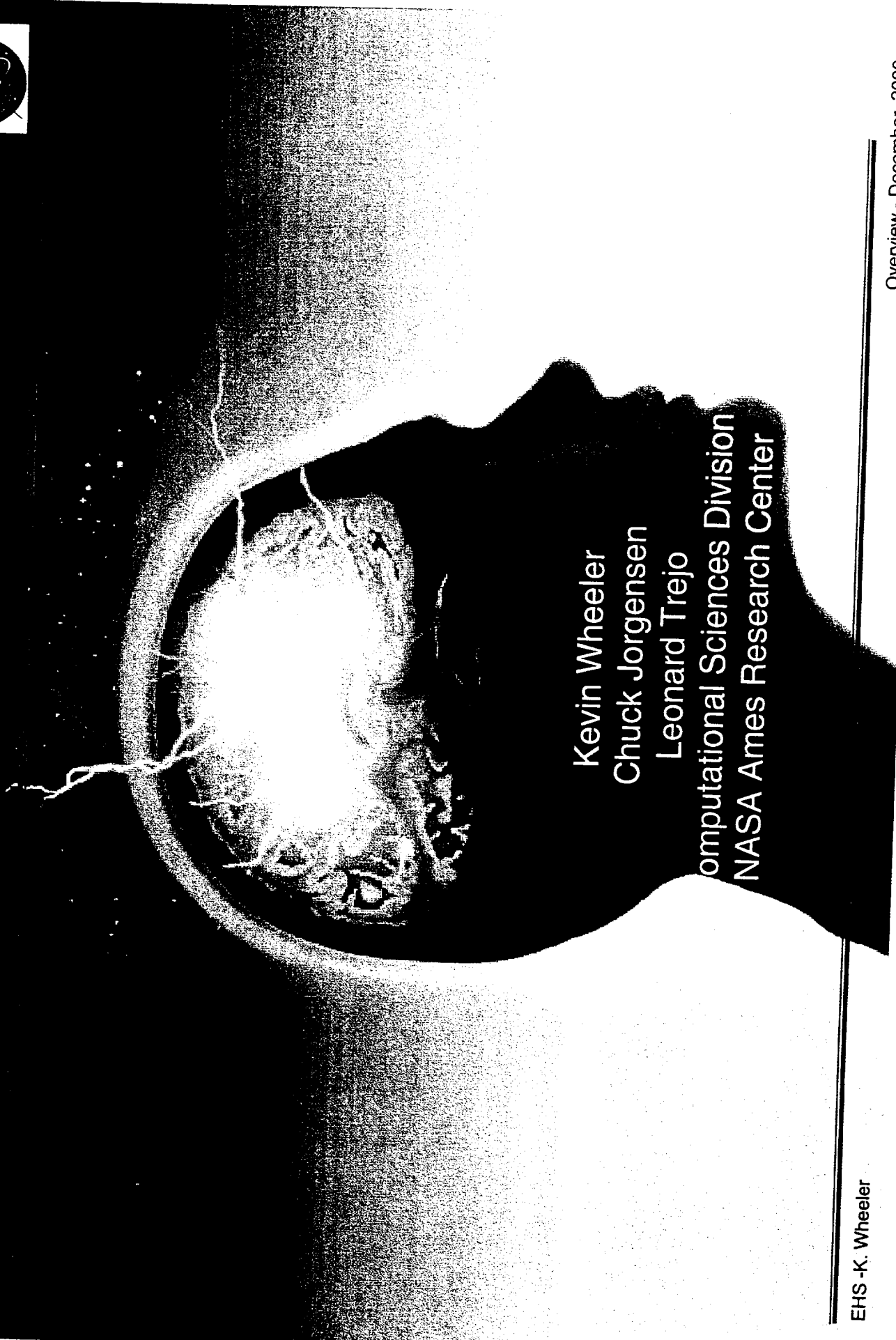
**Figure 1.** Flying F15 active aircraft simulation with dry electrode EMG sleeve.



**Figure 2.** Raw EMG data for two different gestures, typing '8' and typing '9'.



# Neuro-electric Virtual Devices



Kevin Wheeler  
Chuck Jorgensen  
Leonard Trejo  
Computational Sciences Division  
NASA Ames Research Center



# Overview



- Extension of Human Senses Program
- EMG Signal Acquisition & Experiment Design
- EMG Signal Processing & Recognition Approach
- Wearable EMG Hardware
- Bioelectric Joystick and Keyboard Film



# Extension of Human Senses Trends in Personal Computing

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Laptops and PDAs have been evolving as follows:

Larger screens - size limited by carrying convenience, can be replaced by active display glasses.

Smaller, faster motherboards - wearable cases

Spoken command input - speech recognition works for common words but not good for programming and science tasks

Full size keyboards - Design has NOT evolved. The physical size of input keys limits the evolution of cell phones, laptops, command panels, aircraft instrumentation ...



# Extension of Human Senses

## Bioelectric Keyboard NASA Applications

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Wearable Cockpit - virtual instrumentation, moves with pilot, works for AUVs and manned missions.  
Provides for faster and cheaper reconfiguration, and safety monitoring of pilots.

Spacesuit restricted typing - allows for typed data entry while wearing spacesuit or within confined environments.

Natural robotic arm interface - joystick can be replaced with a more natural interface.

Exoskeleton EMG interface - provides capability of working in extreme environments and maneuvering heavy items. Provides for training exoskeleton to do tasks autonomously.



# Extension of Human Senses

## Electrode Types & Locations

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### Electrode Types:

- *Wet temporary* - Ag/Ag Cl stick on temporary electrodes
- *Wet gel/metal cups* - attached with super glue
- *Dry* - metallic composition affixed by elastic

### Electrode Positions:

- *Broad gestures* - large muscle groups, similar across people
- *Finer gestures* - proper position requires spatial over-sampling with reduction.

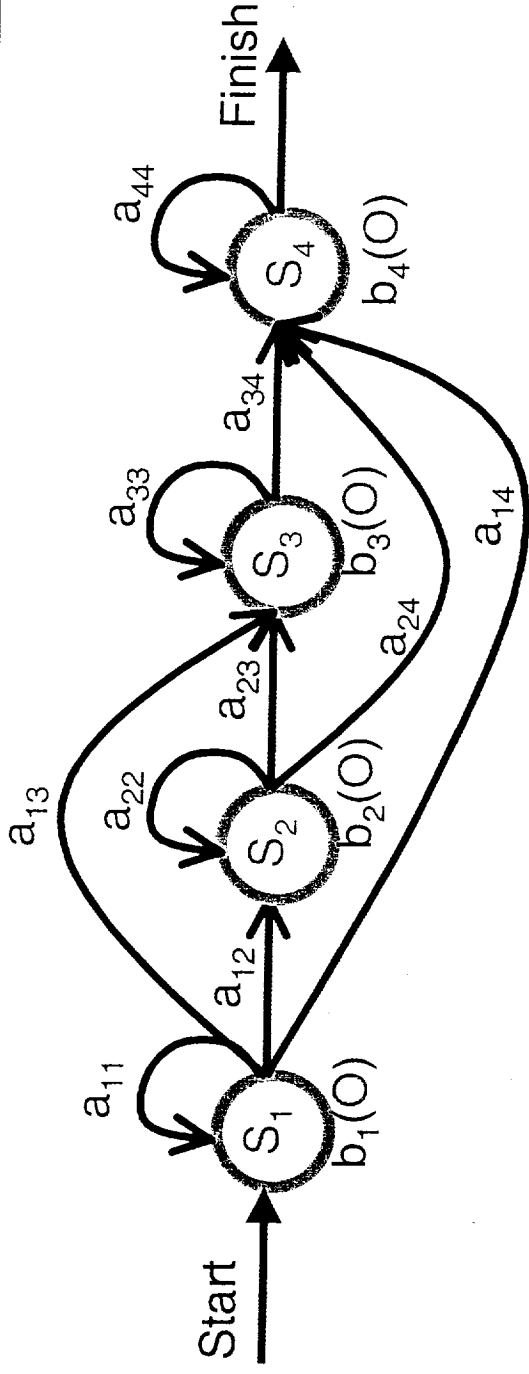
### Example Placement:

- *Joystick* - four electrode pairs on forearm
- *Typing* - eight electrode pairs on forearm



# Extension of Human Senses

## Hidden Markov Models



$a_{ij}$   $P(q_{t+1}=S_j|q_t=S_i)$  transition probability from state  $i$  to state  $j$

$b_j(O) = P(O|q_t=S_j)$  probability of observation when in state  $j$  at time  $t$

$S_j$  State  $j$ ,  
 $\pi_j$  probability of state  $j$

$$b_j(O) = \sum_{m=1}^M c_{jm} N [O, \mu_{jm}, \Sigma_{jm}], \quad \text{mixture model}$$





# Extension of Human Senses

## Hidden Markov Model Overview



### Initialization -

The initial state probability densities are formed with variance based state partitioning with per state clustering.

### Features -

Overlapping moving averages of the absolute values of the signals.

### Training -

Standard Baum-Welch training is employed.

### Recall -

Viterbi based recall is used.

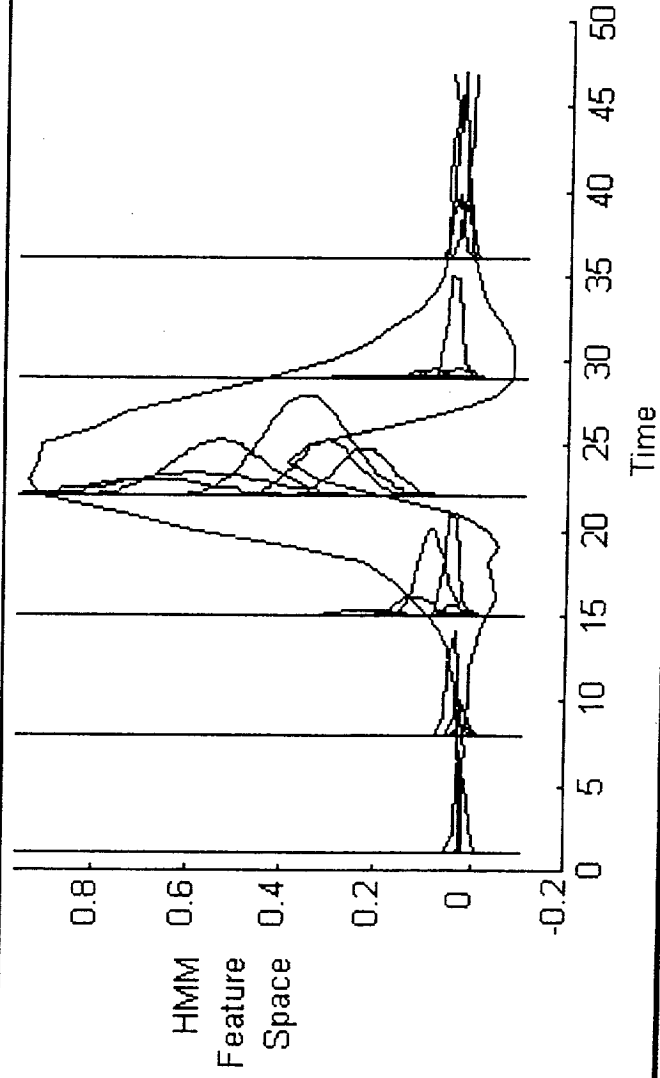
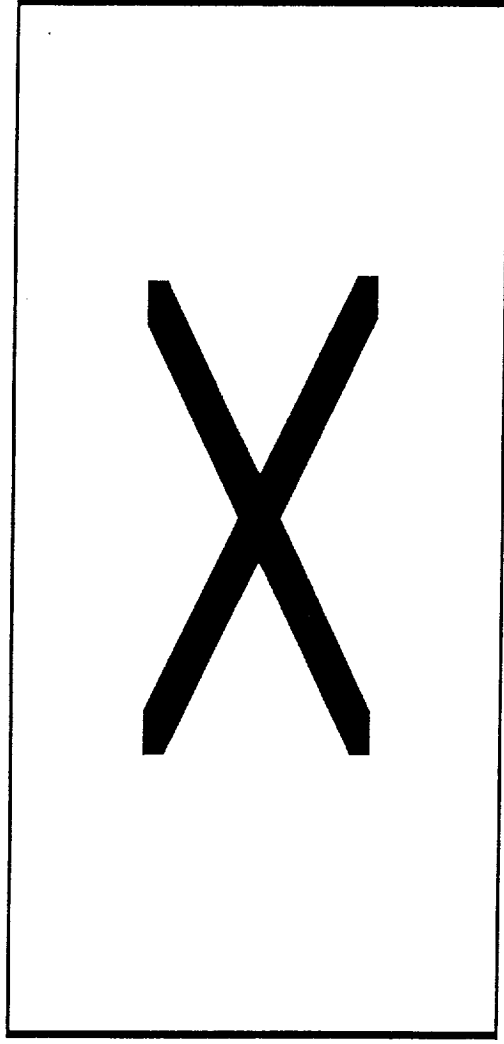
### Real-time Recall -

Uses multiple identical recognitions in a row.



# Extension of Human Senses

## HMM Initialization





# Extension of Human Senses

## Inference Models

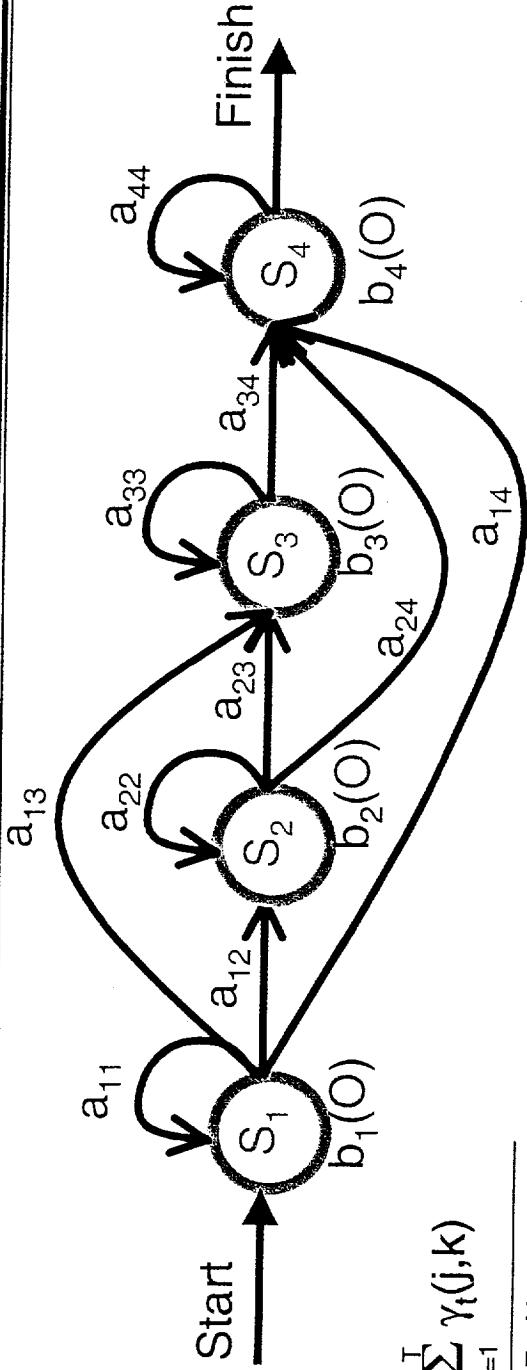


Real World Problem Domain:	Quick & Dirty Tradeoffs:
<ul style="list-style-type: none"><li>• Non-stationary time-series</li><li>• Non-Gaussian distributions of feature values</li><li>• Dependence between features and channels</li><li>• Real-time recall requirement</li><li>• On-line adaptation capability</li><li>• Multi-user context switching</li></ul>	<ul style="list-style-type: none"><li>• Short time windows and transforms</li><li>• Mixtures, Gram-Charlier, Multi-scale</li><li>• Eliminate via mutual information</li><li>• Exp() macros, focused computations</li><li>• Vary as little as possible</li><li>• Simple voting schemes</li></ul>



# Extension of Human Senses

## HMM Training



$$C_{jk} = \frac{\sum_{t=1}^I \gamma_t(j,k)}{\sum_{t=1}^I \sum_{m=1}^M \gamma_t(j,m)}$$

$$\mu_{jk} = \frac{\sum \gamma_t(j,k) * O_t}{\sum \gamma_t(j,k)}$$

$$\Sigma_{jk} = \frac{\sum_{t=1}^I \gamma_t(j,k) * (O_t - \mu_{jk})(O_t - \mu_{jk})^T}{\sum_{t=1}^I \gamma_t(j,k)}$$

$$\gamma_t(j,k) = \frac{\alpha_t(j) \beta_t(j)}{\sum_{j=1}^N \alpha_t(j) \beta_t(j)} \frac{C_{jk} N(O_t, \mu_{jk}, \Sigma_{jk})}{\sum_{m=1}^M C_{jk} N(O_t, \mu_{jk}, \Sigma_{jk})}$$

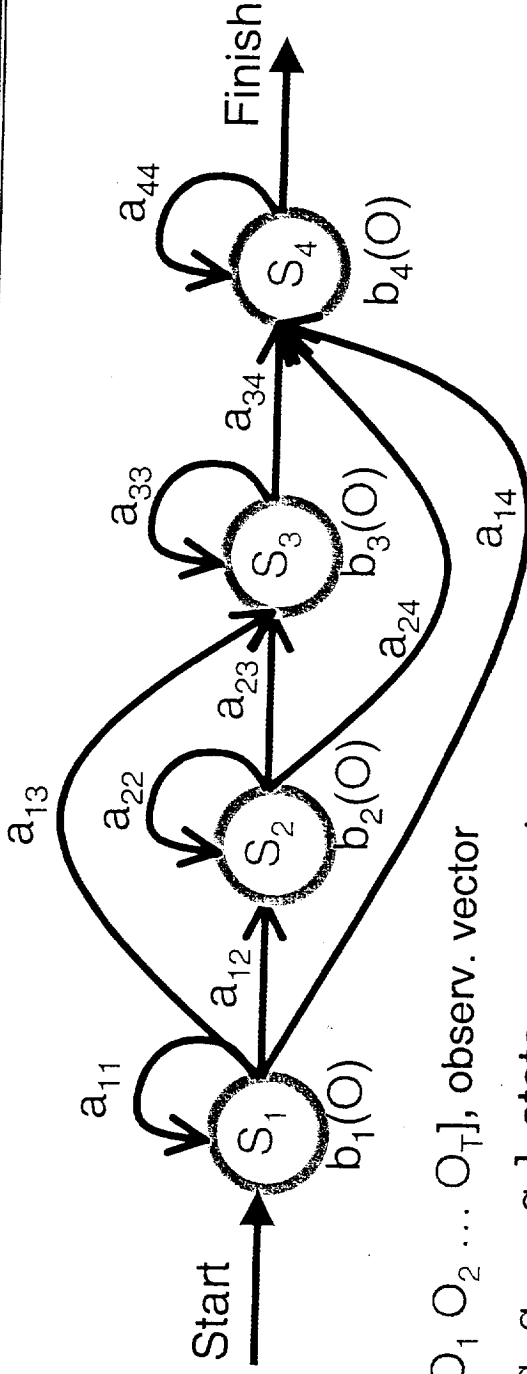
$$\xi_t(i,j) = \frac{\alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}{\sum_{t=1}^I \xi_t(i,j)} \frac{P(O|\lambda)}{\sum_{t=1}^I \xi_t(i,j)}$$

$$a_{ij} = \frac{\sum_{j=1}^{N_{I-1}} \xi_t(i,j)}{\sum_{j=1}^{N_{I-1}} \sum_{t=1}^I \xi_t(i,j)}$$



# Extension of Human Senses

## Viterbi Recall



$O = [O_1 O_2 \dots O_T]$ , observ. vector

$Q = [q_1 q_2 \dots q_T]$ , state seq. vector

$$P(Q|\lambda) = \pi_{q_1} a_{q_1 q_2} a_{q_2 q_3} \dots a_{q_{T-1} q_T}$$

$$P(O|Q, \lambda) = b_{q_1}(O_1) b_{q_2}(O_2) \dots b_{q_T}(O_T)$$

$$P(O|\lambda) = \sum_{\text{all } Q} P(O|Q, \lambda) P(Q|\lambda)$$

$$P(O|\lambda) = \sum_{q_1, q_2, \dots, q_T} \pi_{q_1} b_{q_1}(O_1) a_{q_1 q_2} b_{q_2}(O_2) \dots a_{q_{T-1} q_T} b_{q_T}(O_T)$$

$$\text{i) } \alpha_1(i) = \pi_i b_i(O_1) \quad 1 \leq i \leq N$$

$$\text{ii) } \alpha_{t+1}(j) = [\sum_i \alpha_t(i) a_{ij}] b_j(O_{t+1}) \quad 1 \leq t \leq T-1$$

$$\text{iii) } P(O|\lambda) = \sum \alpha_T(i)$$



# Extension of Human Senses Visualization & Understanding



## Areas of Understanding

### Error Analysis

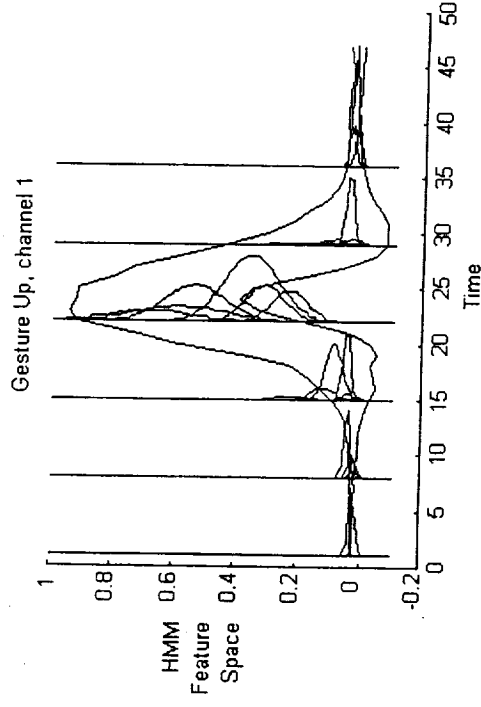
- ROC curves
- Confusion Matrix
- Error vs. parameters

### Data Domain

Alternative views  
such as this  
multi-day plot.



### Models



### English Explanations

Automated transformation from  
model space to words:  
*Typing one is best separated from  
typing five by channel 6 time slice 4.*



# Extension of Human Senses Typing Demonstration



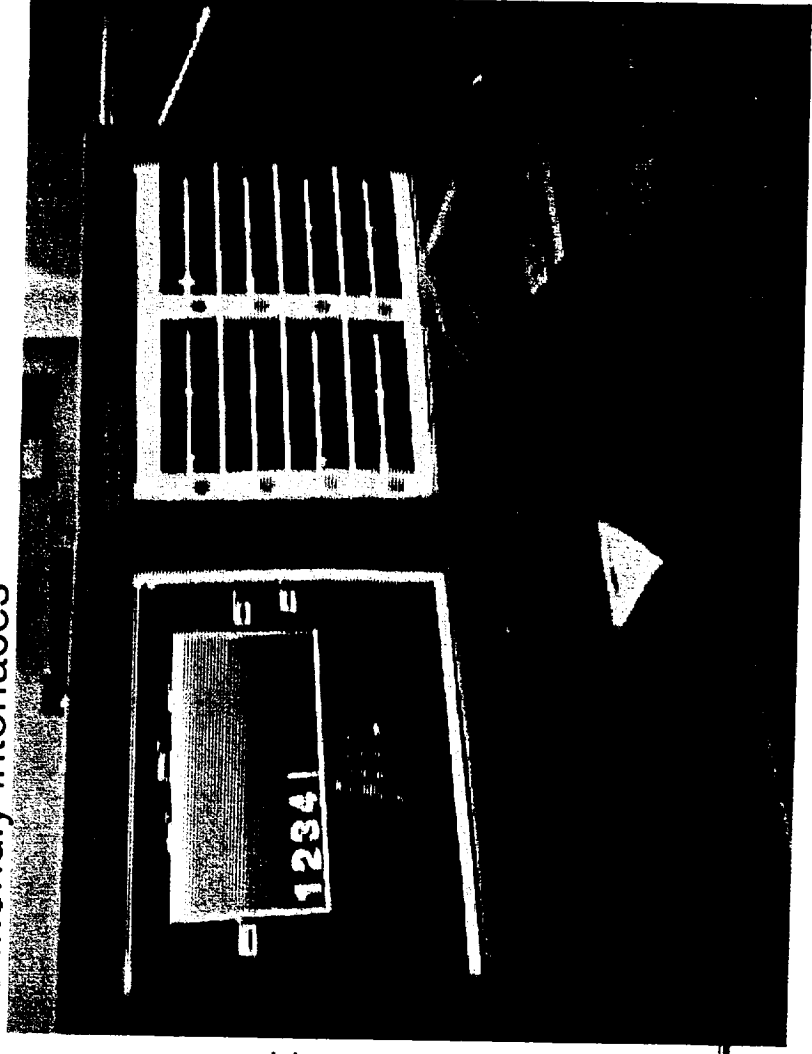
Demonstration: Eight channels of EMG are recognized as keystrokes when pretending to type on a keyboard number pad.

Purpose:

- qwerty keyboard is not the ultimate interface but it is most familiar
- alternative typing methods require additional user training
- hands are free of gloves and other apparatus
- typing capability leads to other more friendly interfaces

Issues:

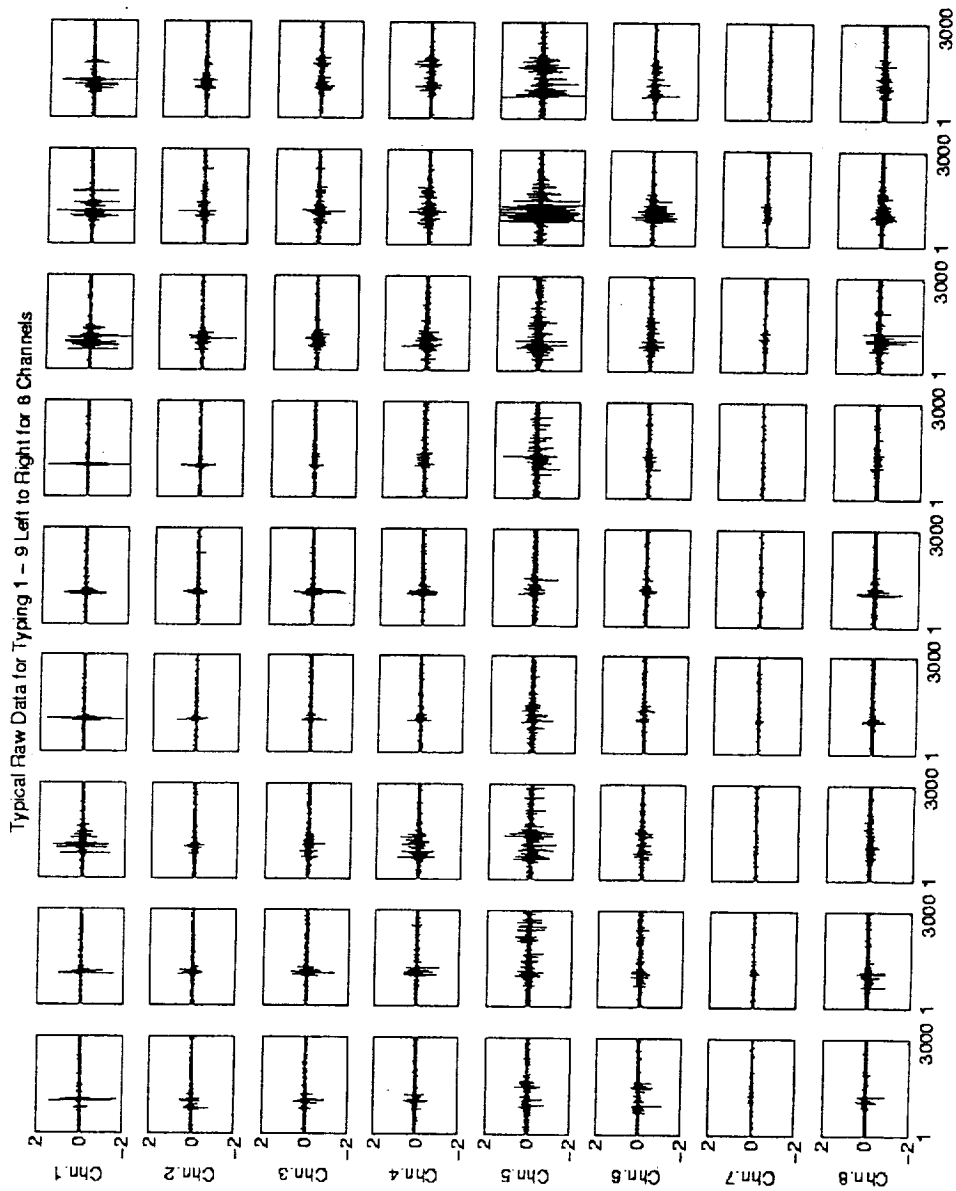
- Typing style is critical
- Finer gestures need adjustment to individual
- Small sensor development





# Extension of Human Senses

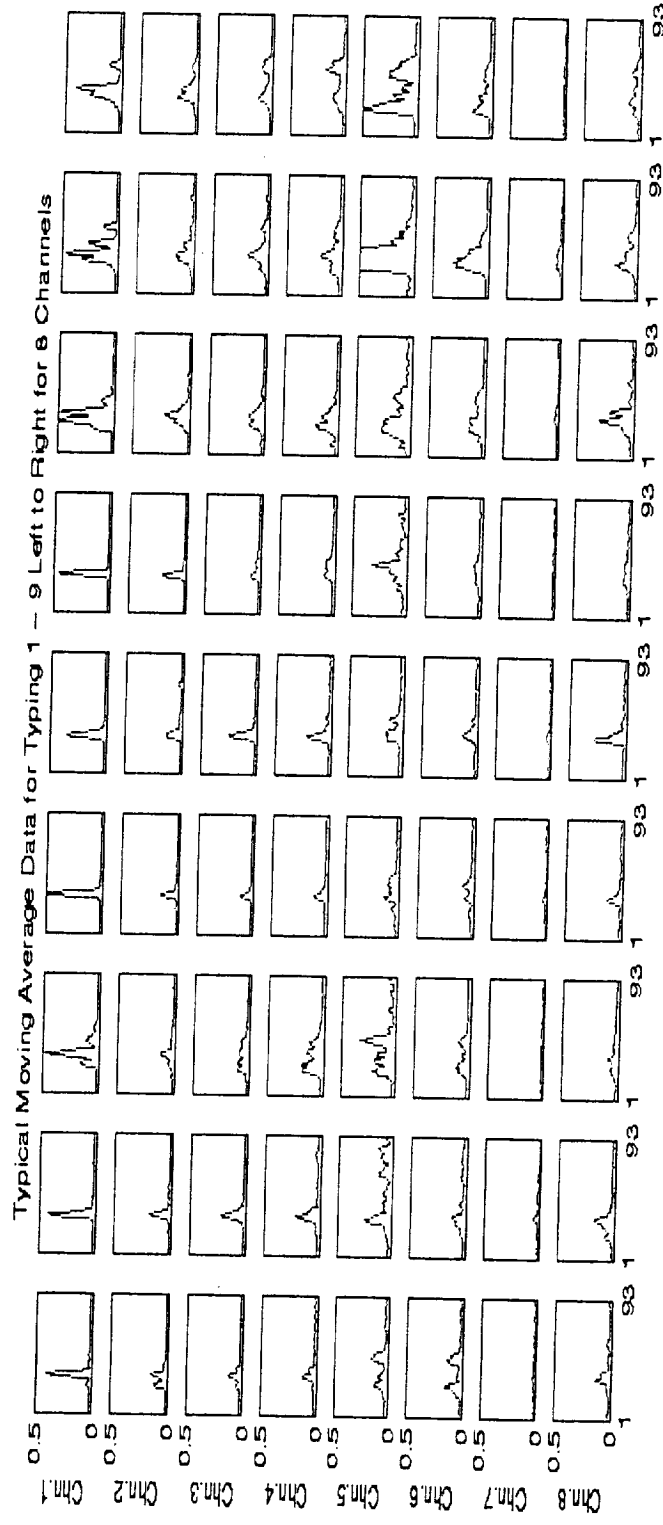
## Typing Data





# Extension of Human Senses

## Typing Data





# Extension of Human Senses Mutual Information Analysis



Mutual information measures how independent two random events are by using the information contained in their probability distributions.

In the numeric pad typing example, the independence of the time-sliced data can be measured in a number of different ways:

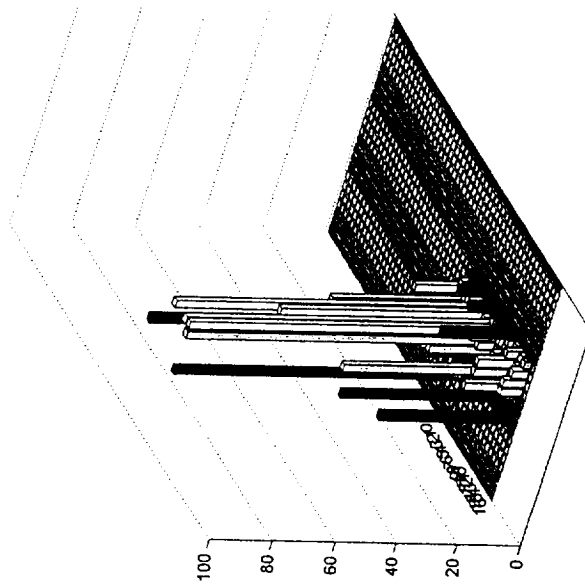
Single Time Single Channel (STSC) - one time-slice and channel for gesture X can be compared with the same time and channel for gesture Y.

Multi-Time Single Channel (MTSC) - one time-slice and one channel for gesture X can be compared with all time slices and the same channel for gesture Y.

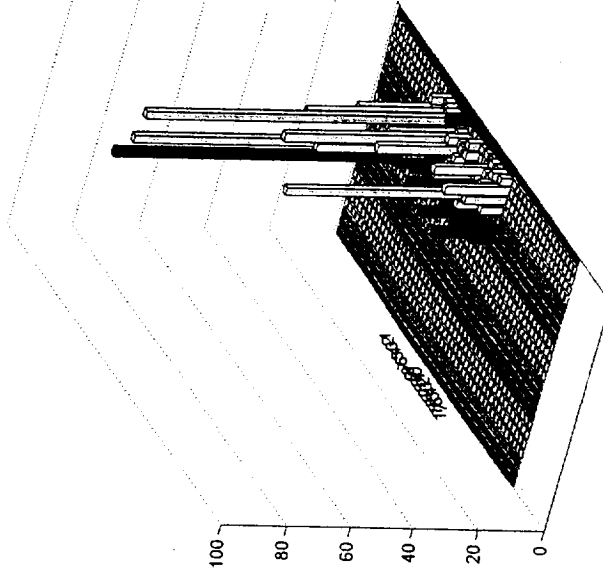
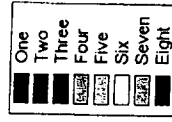
Multi-Time Multi-Channel (MTMC) - one time-slice and one channel for gesture X can be compared with all time slices and all channels for gesture Y.



# Extension of Human Senses Mutual Information (STSC)



Comparing independence for pressing "1" with pressing "3" for each channel across time.



Comparing independence for pressing "4" with pressing "6" for each channel across time.

Note that different channels are important at different times for distinguishing between key presses. For "1" vs. "3" channels 5 and 6 are important, for "4" Vs. "6" channels 4 and 7 are significantly different.

