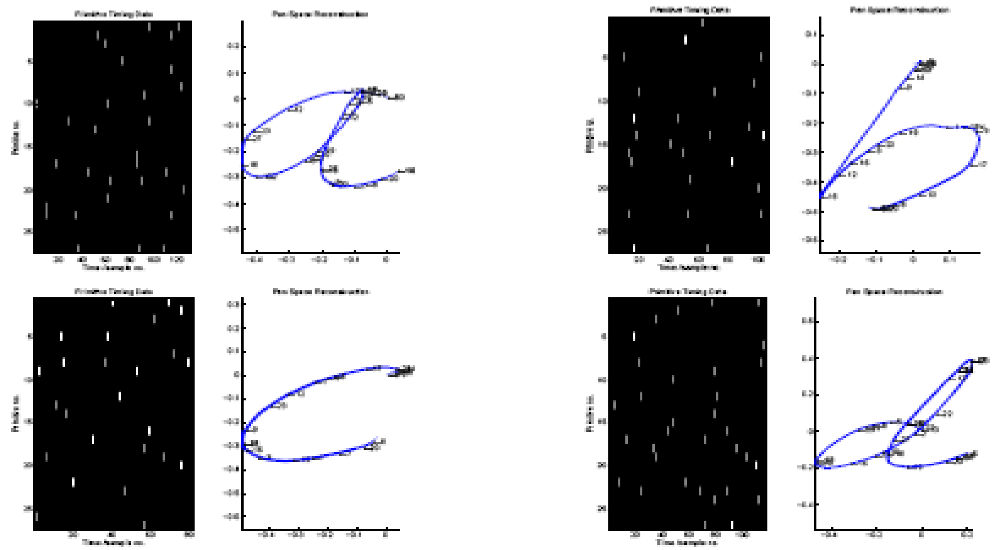
IJCAI 2007

6th - 12th January

A Primitive Based Generative Model to Infer Timing Information in Unpartitioned Handwriting Data



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Talk Overview

- Background / Motivation
  - Motor Primitive evidence
  - Extraction methods
- Model outline
  - Piano Model / fHMM
  - Implementation
  - Timing Models
- Data and Demos
- Conclusions

Motor Primitives

- Movement problem / Motor planning
- Bizzi – Modular forcefields
- Wolpert – Reaching and grasping
- Konczak – Primitives and reflex reactions
- Lewicki – Auditory features

Bizzi Spinal Forcefields

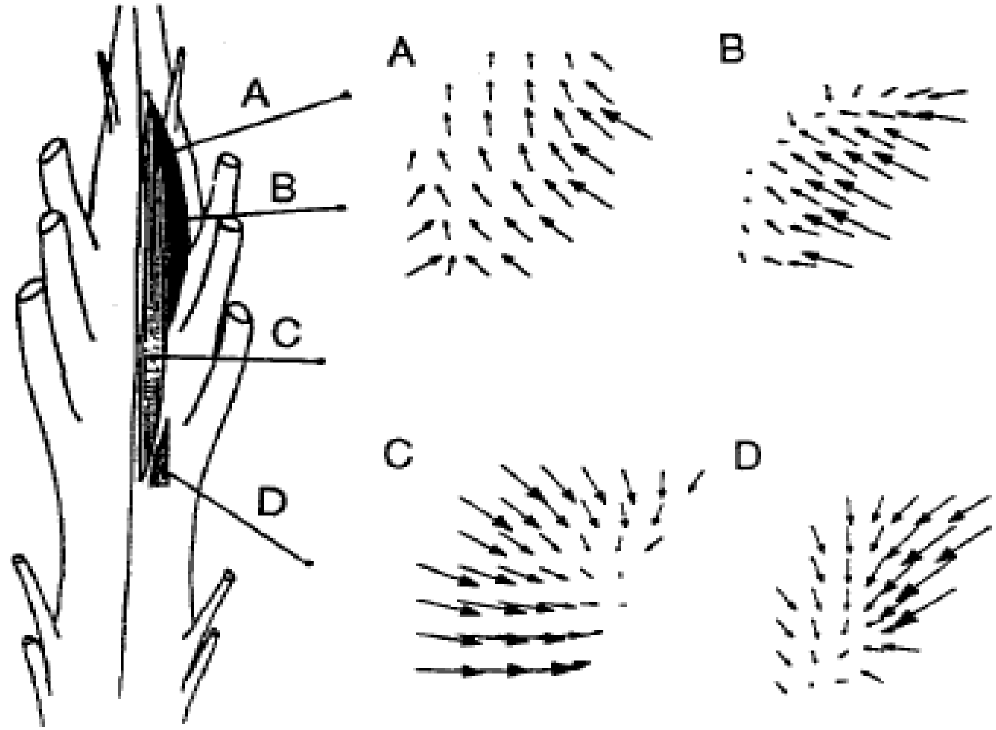
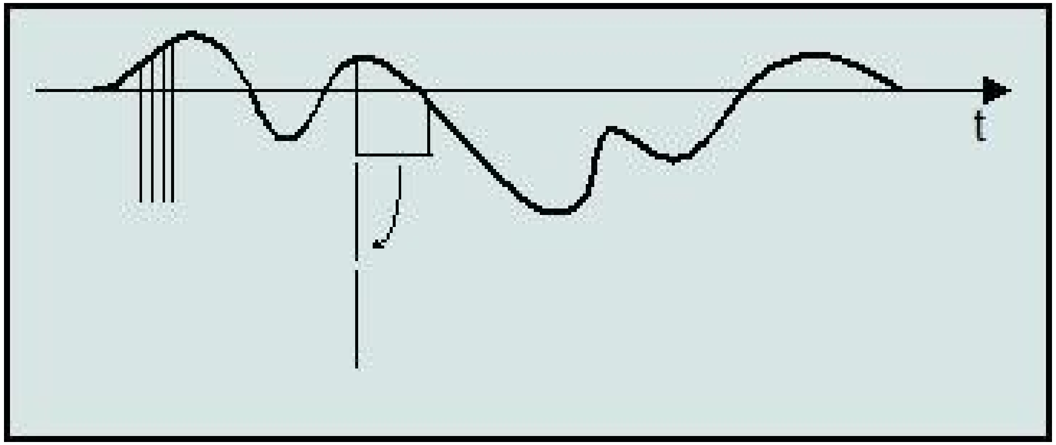


Fig. 2. *Convergent force fields (CFFs).* **(Left.)** *Regions of the lumbar spinal cord that contain the neural circuitry that specifies the force fields (A–D). Within each region, similar sets of CFFs are produced. The diagram is based on 40 CFFs that were elicited by microstimulation of premotor regions in three frogs with transected spinal cords.* **(Right.)** *Four types of CFFs. To facilitate comparison among CFFs that were recorded in different animals, the passive force field was subtracted from the force field that was obtained in the steady state.* Reproduced from Ref. 6.

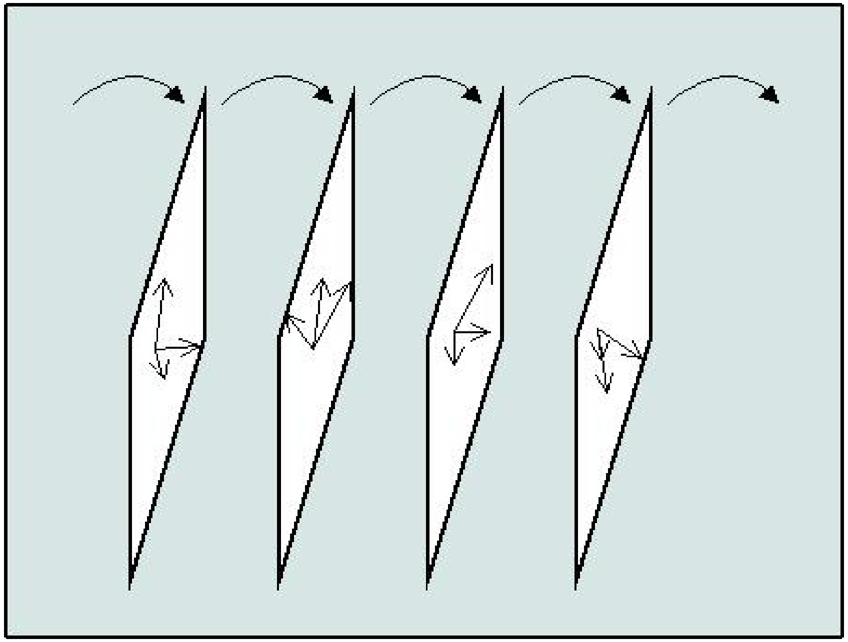
Bizzi *et al* (1995) Modular Organisation of motor behaviour in the frog's spinal cord. *Trends in Neurosciences*

Extracting primitives from data

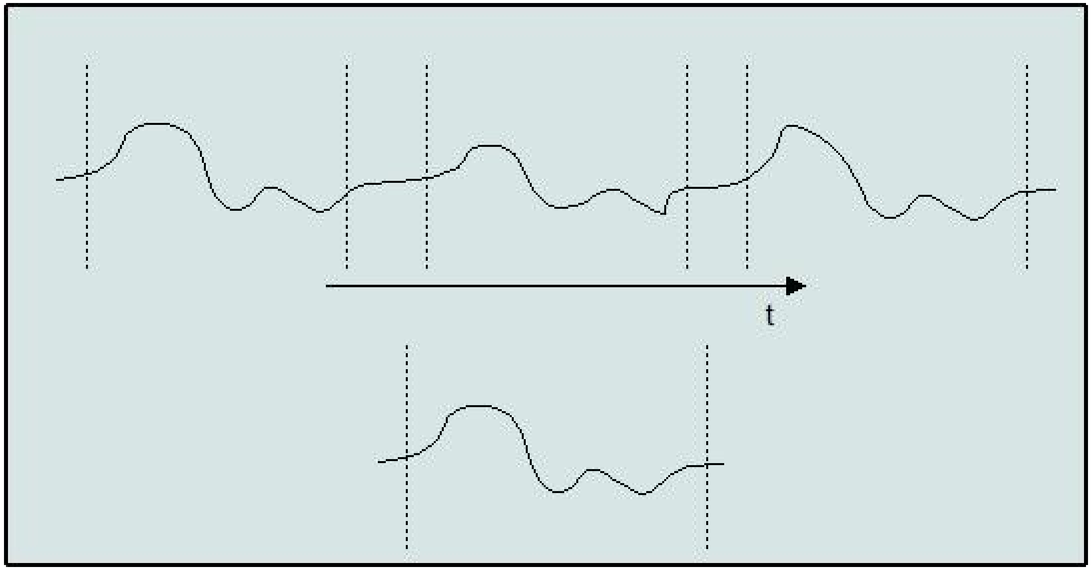
- ICA
  - Time slice
  - Spatio-temporal



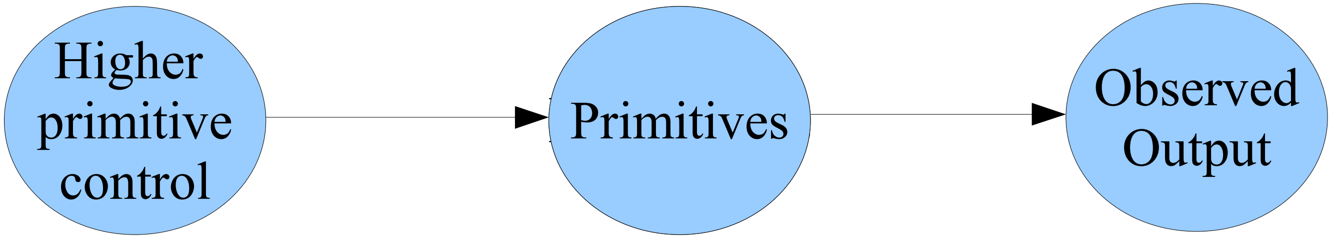
- Unconstrained HMM



- Data motif extraction

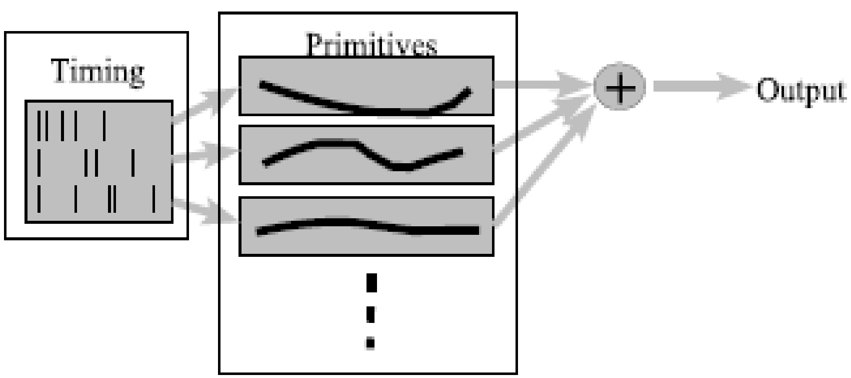


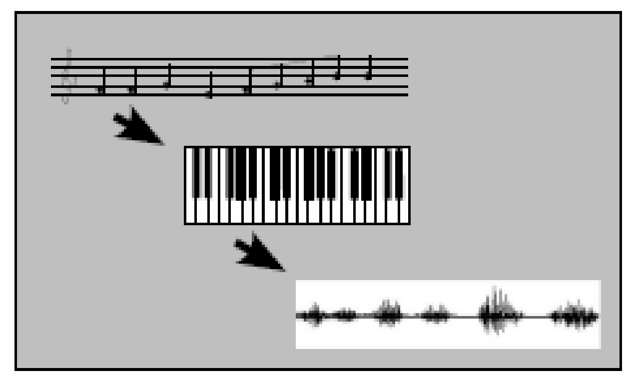
- Generative probabilistic model



Generative Model: The Piano Model

- We take a generative approach to modelling Motor Primitives.
- Assume that the primitives are time extended blocks of movement, that can be superimposed without timing restrictions.

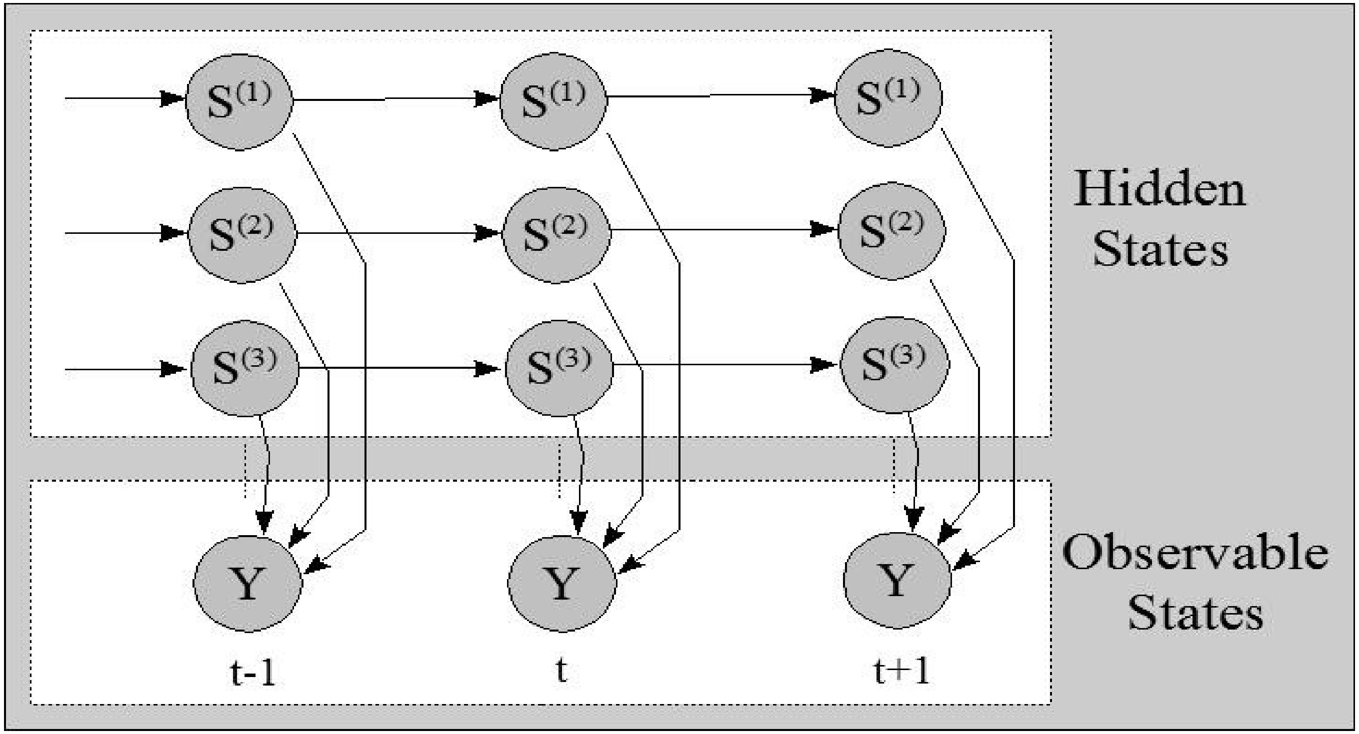




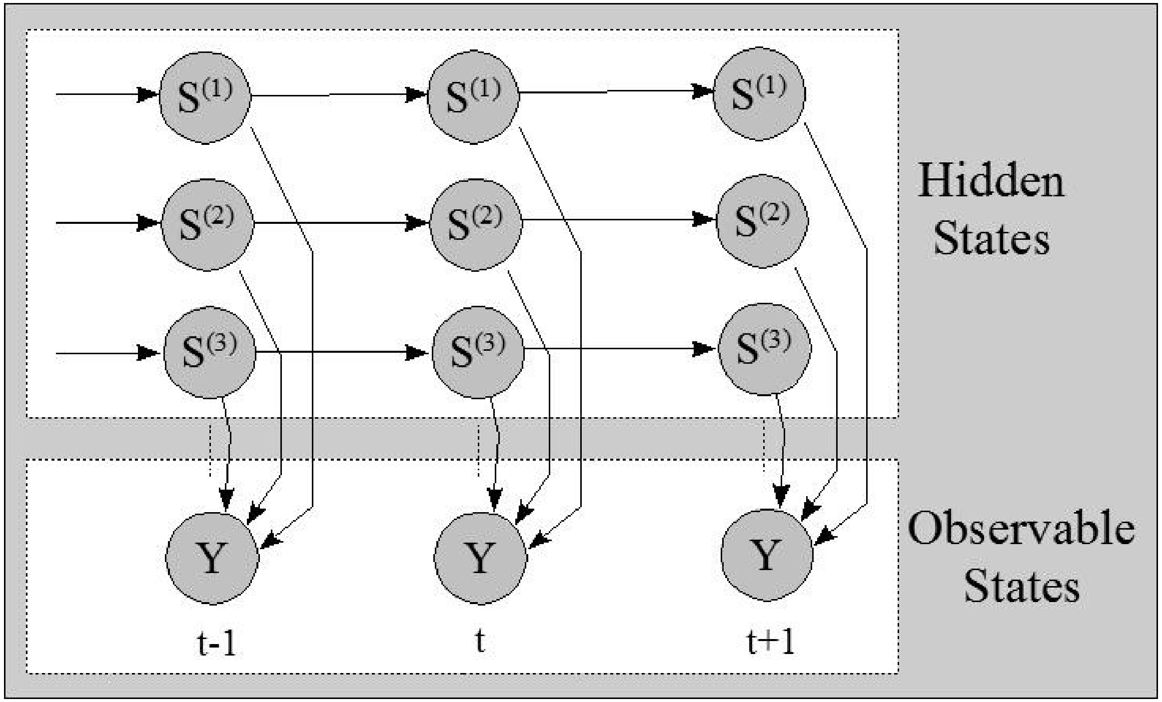
$$Y(t) = \sum_{m,n} \alpha_{mn} W_m(t - \tau_{mn})$$

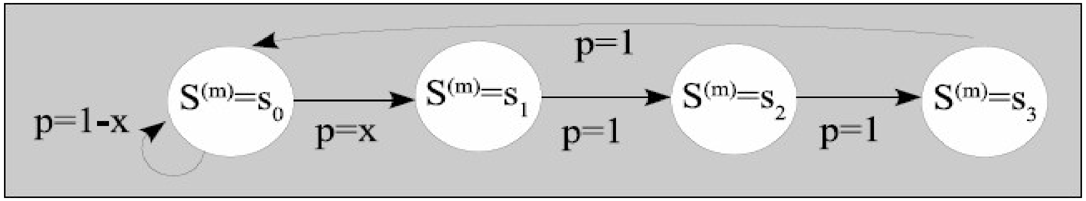
Probabilistic Framework: Factorial Hidden Markov Model

- Presence of noise in data requires a probabilistic framework to learn the parameters for the model.
- Factorial Hidden Markov Model (fHMM) was chosen.



- Each factor models one primitive
- Model constraints:
  - Output contribution of state 0 must be zero.
  - State transitions constrained to be monotonic.
- Partitioning of model:
  - Timing Part (Hidden state expectations)
  - Primitive Part (Model parameters)
- Expectation-Maximisation

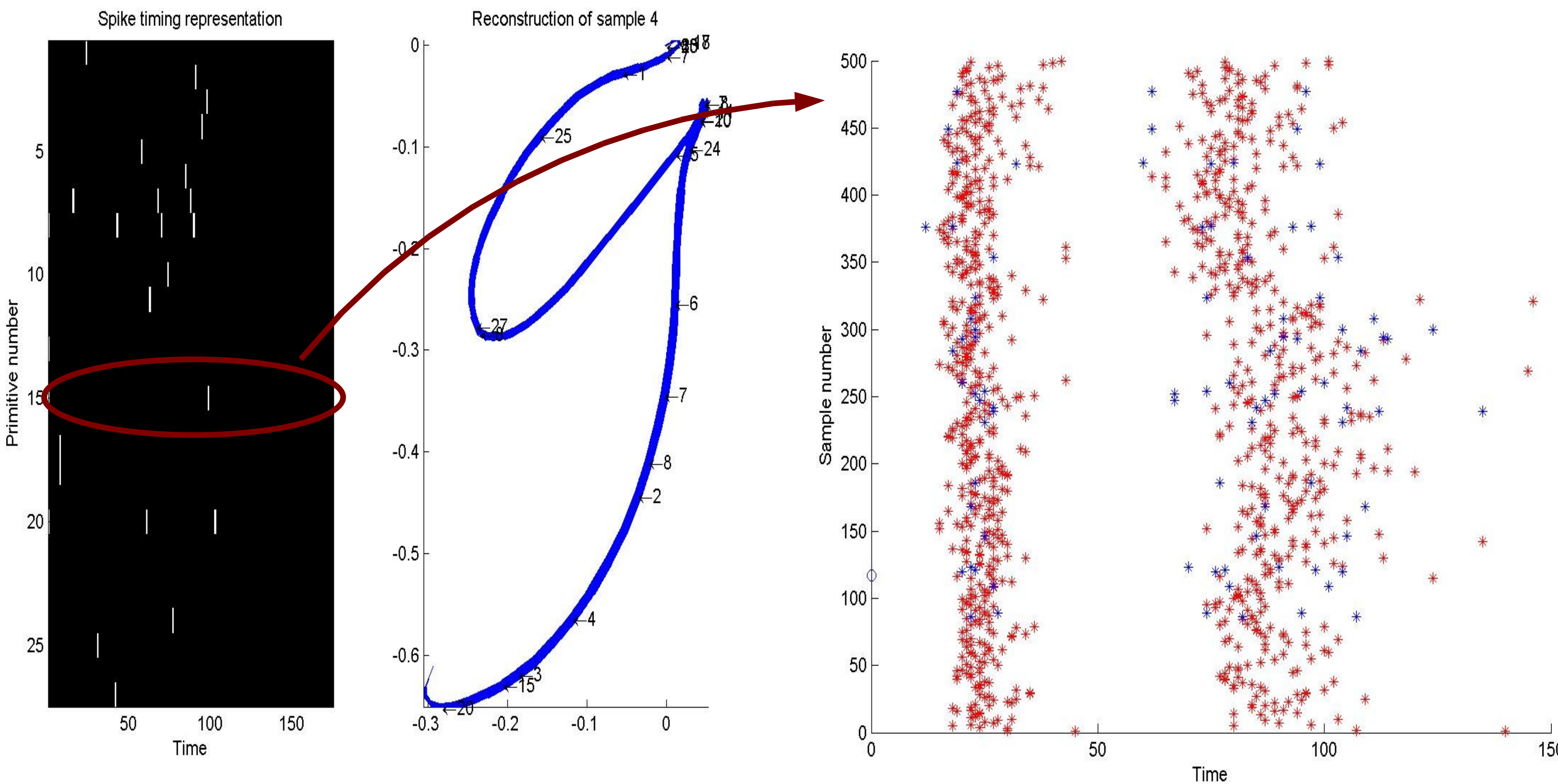




Hidden state representation

Single character

All characters

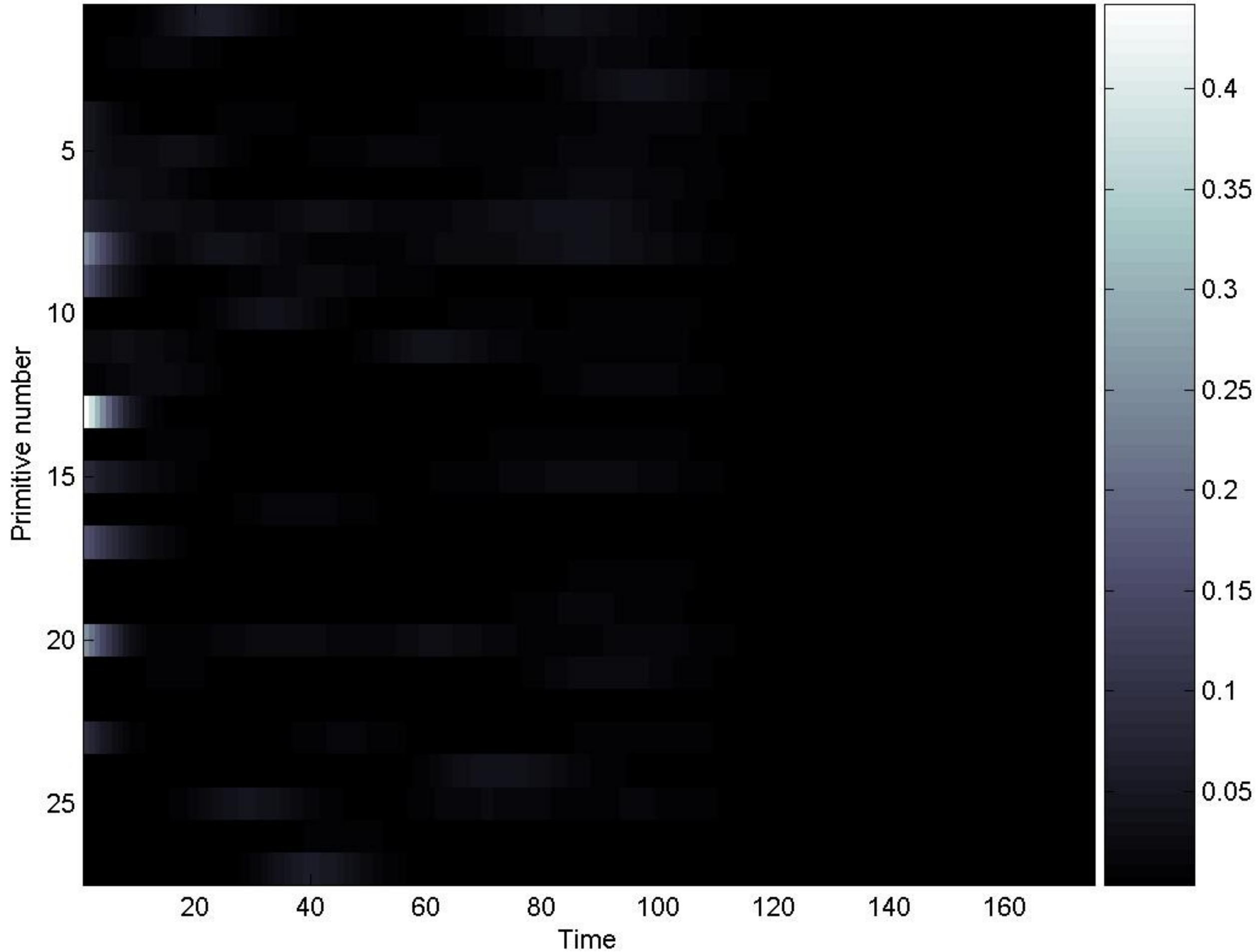


Timing Model

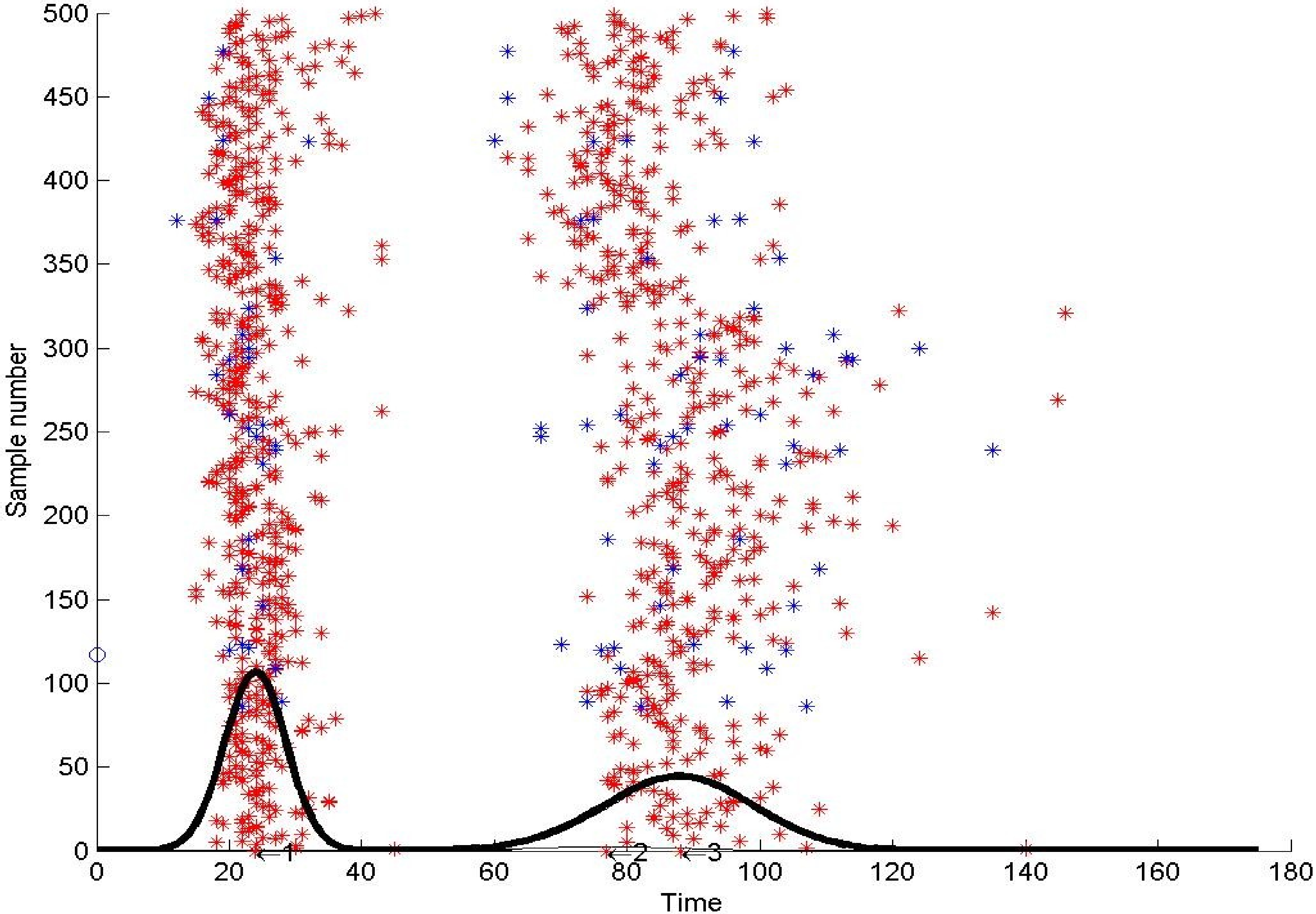
- Constraints placed upon fHMM allow spike timing representation for hidden states
- Model for spike timing to encode higher level character description
- Each primitive can be used (producing a spike) more than once, but not a fixed number of times
- Simple Gaussian representations have a problem of varying dimensionality of data
- Concatenating all the data looses the spike ordering, but allows a mixture of Gaussians model

Timing Model Summary

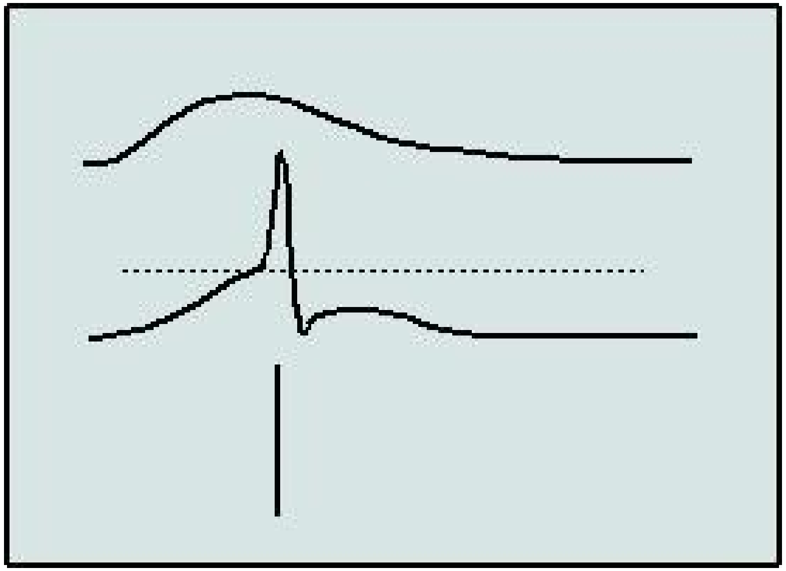
- Independent spikes model
  - i.i.d. Spikes $P(s)=\Pi_t P(s_t)$



- Gaussian / Mixture of Gaussians model
  - Spike times drawn from independent MoG model
  - $P(s)=P(s|k).P(k)$, $P(s|k)\sim N(\mu,\sigma^2)$, k Gaussians

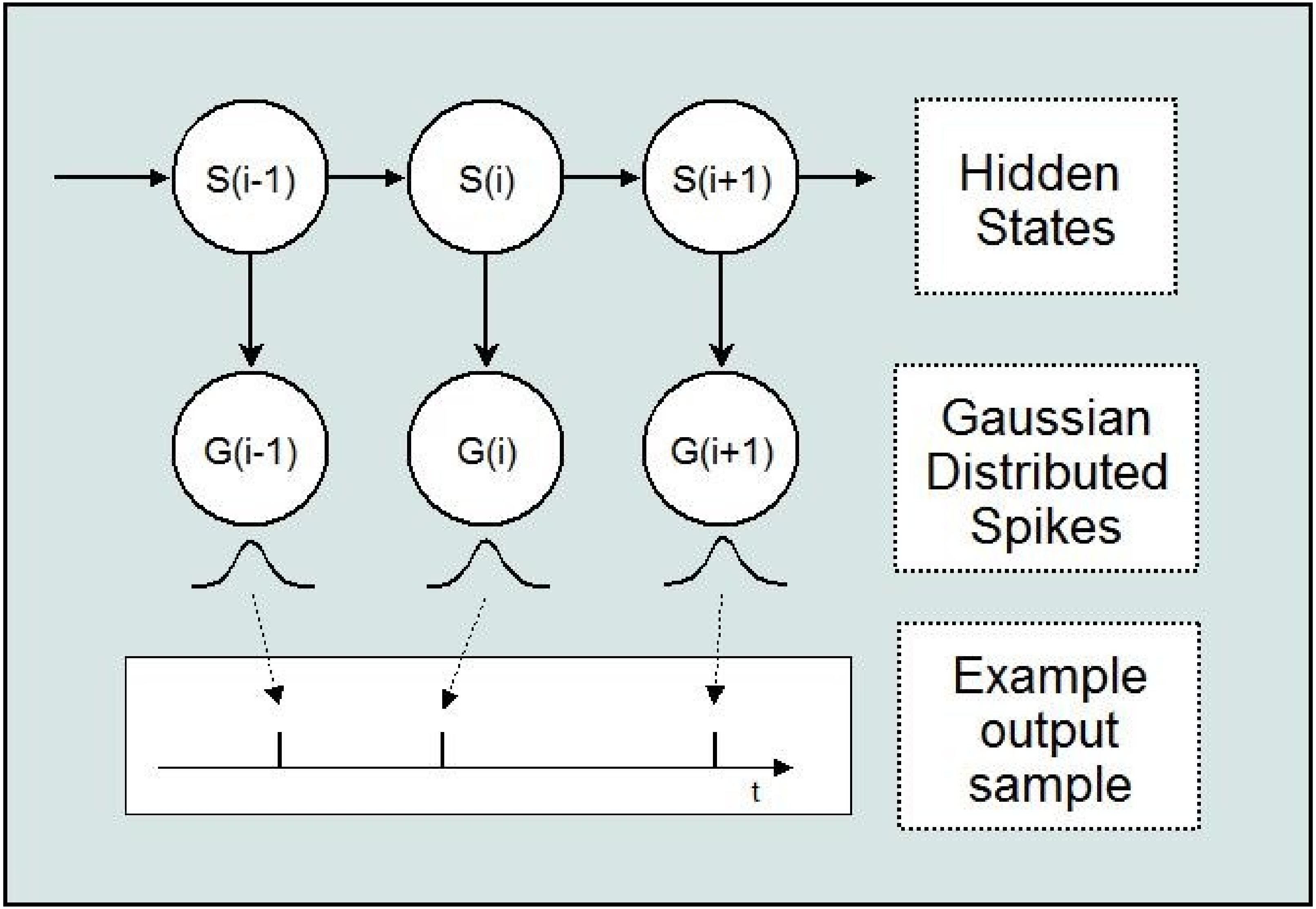


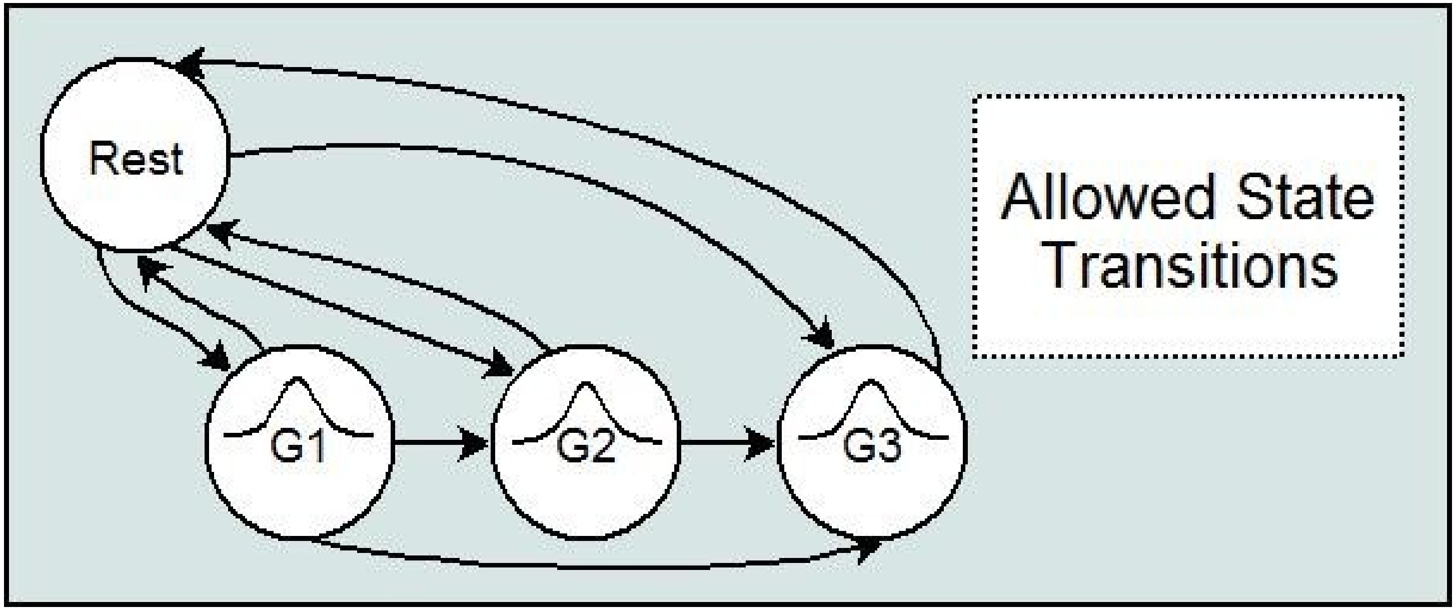
- Integrate and Fire model
  - Biologically inspired approach

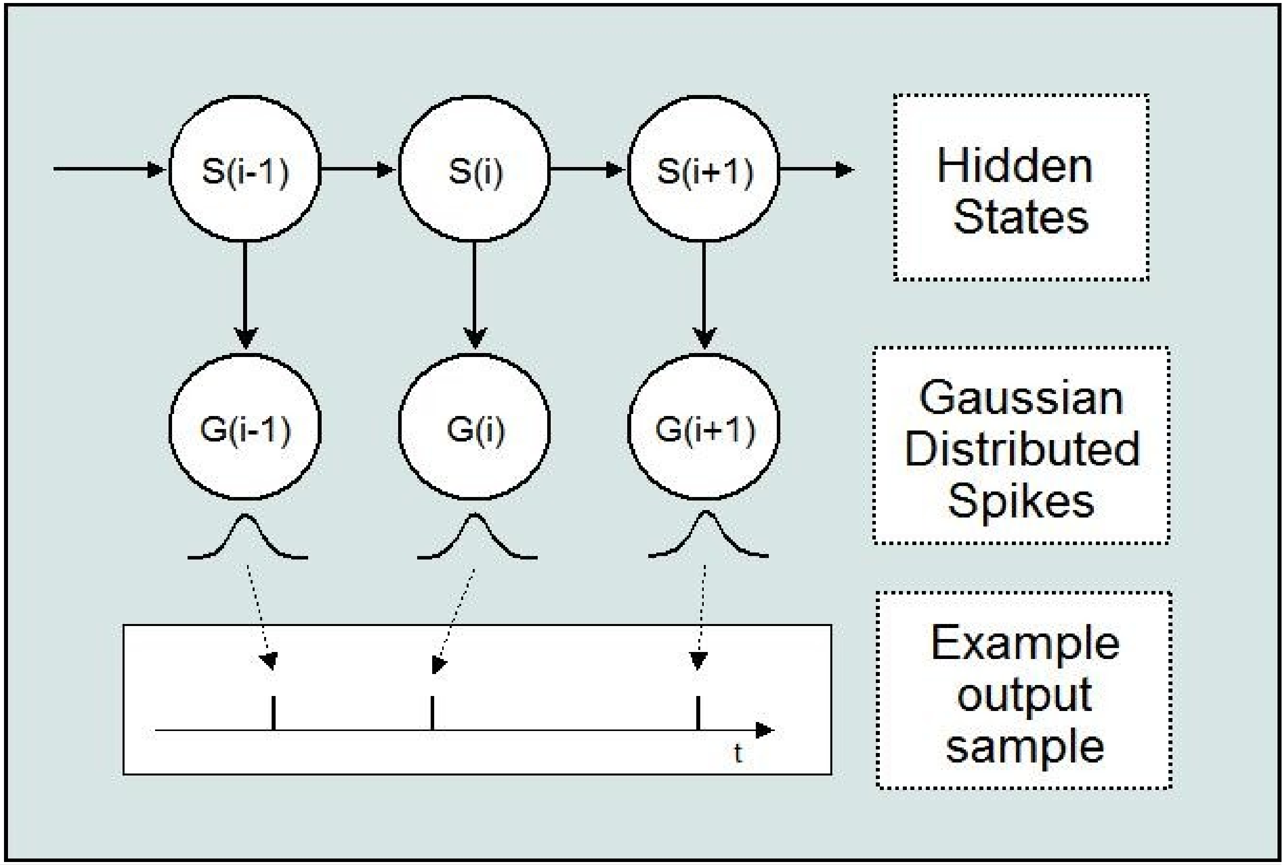


- Probabilistic model for timing of spikes, presence of spikes, and interdependence between spikes (and primitives possibly)
  - Hidden Markov Model captures short term dependence and long term independence, and can model presence of spikes using hidden states

HMM Timing Model




Rest
G1
G2
G3
Allowed State Transitions


S(i-1)
S(i)
S(i+1)
Hidden States
G(i-1)
G(i)
G(i+1)
Gaussian Distributed Spikes
t
Example output sample

Results

Conclusions / The Future

- Parameter learning without timing constraints
  - Reconstruction of data set
- Timing control
  - Scribbling / Writing
  - Partitioning of model – Primitives / Timing
- Directions
  - Timing model
  - Subject specific style
  - Learning and adaptation
  - Dynamic Primitives (Including feedback)