CARDIFF SCHOOL OF TECHNOLOGIES

Interpolated SOM Neural Networks for Anatomical Joint Constraint Modelling

Dr. Glenn L. Jenkins

CardiffMet

Overview

- Anatomical joint constraint simulations
  - Medical Applications
  - Animation
  - Ergonomics
  - Robot control simulation
- Classification (Engin and Tumner 2004)
  - Phenomenological
  - Biologically Based
- Limitations of existing approaches
  - Abstraction of joint function
  - Rotational representation
  - Discretised output space

Anatomical Joint Constraint Modelling

- Mechanical Approximations
  - Euler Angles (Faraway, Zhang and Chaffin 1999)
- N-Dimensional Boundaries
  - Spherical (Korein 1984)
  - Conical (Engin *et al* 2000)
  - Multiple cones (Maruel *et al* 2000)
- Occupancy Matrix
  - Signed distance cones (Engell-Norregard *et al* 2011)

Anatomical Joint Constraint Modelling

Unit Quaternion Based Approaches

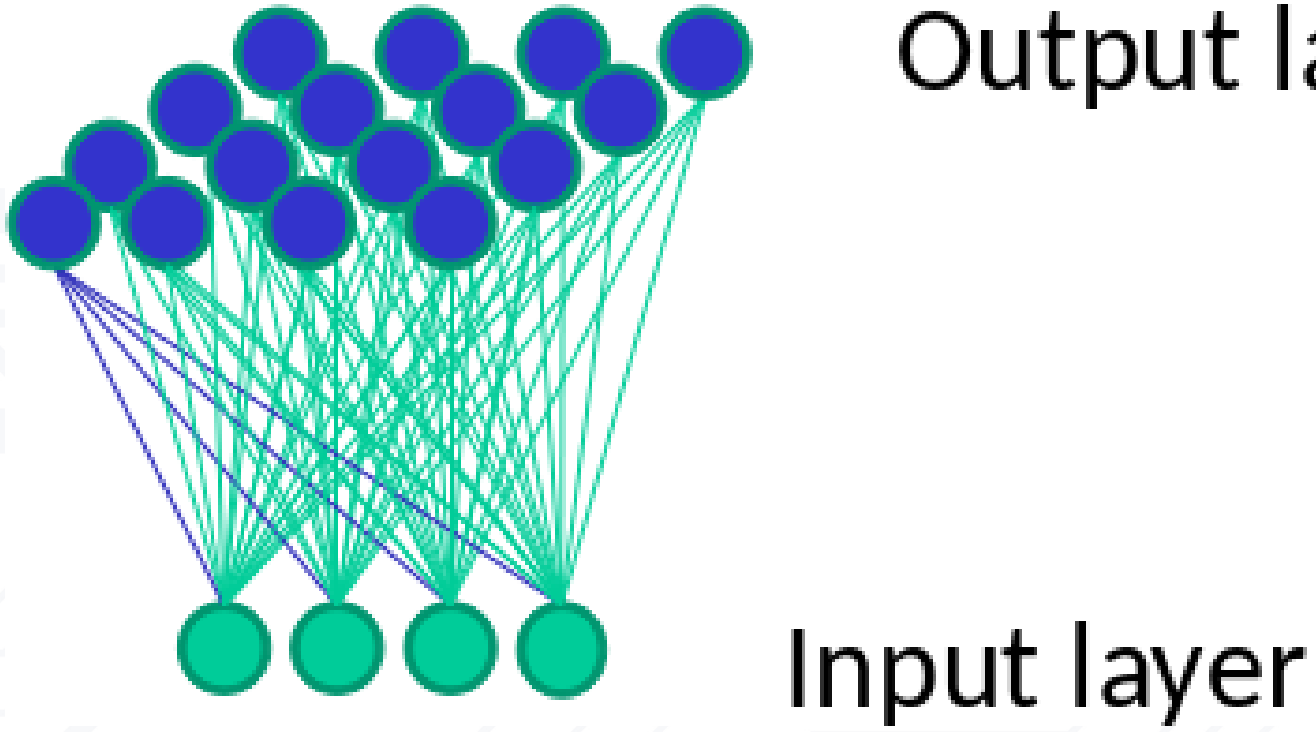
- Decomposition to Axis-Angle (Lee 2000)(Lui & Prakash 2003)
- Iso Surface (Herda *et al* 2003/2004)
- Distribution - $\mathbb{R}^3$ (Johnson 1995) - $\mathbb{S}^3$ (Brau and Jiang 2016)

Machine Learning

- Evolved GMLP (Jenkins *et al* 2006/2011)
- SOM (Jenkins & Dacey 2010)
- UQ-SOM (*ibid* 2014)
- RM (Jenkins *et al* 2016/2017/2019)
- GMLP (Jian and Liu 2018) - Trained from MoCap Database.

Continuous Self Organising Map

- Based on Kohonen Self Organising Map (SOM)
  - Topology preserving projection from n-dimensional input space to two dimensional grid
- Extended to give a continuous output (Göppert and Rosentiel, 1993)



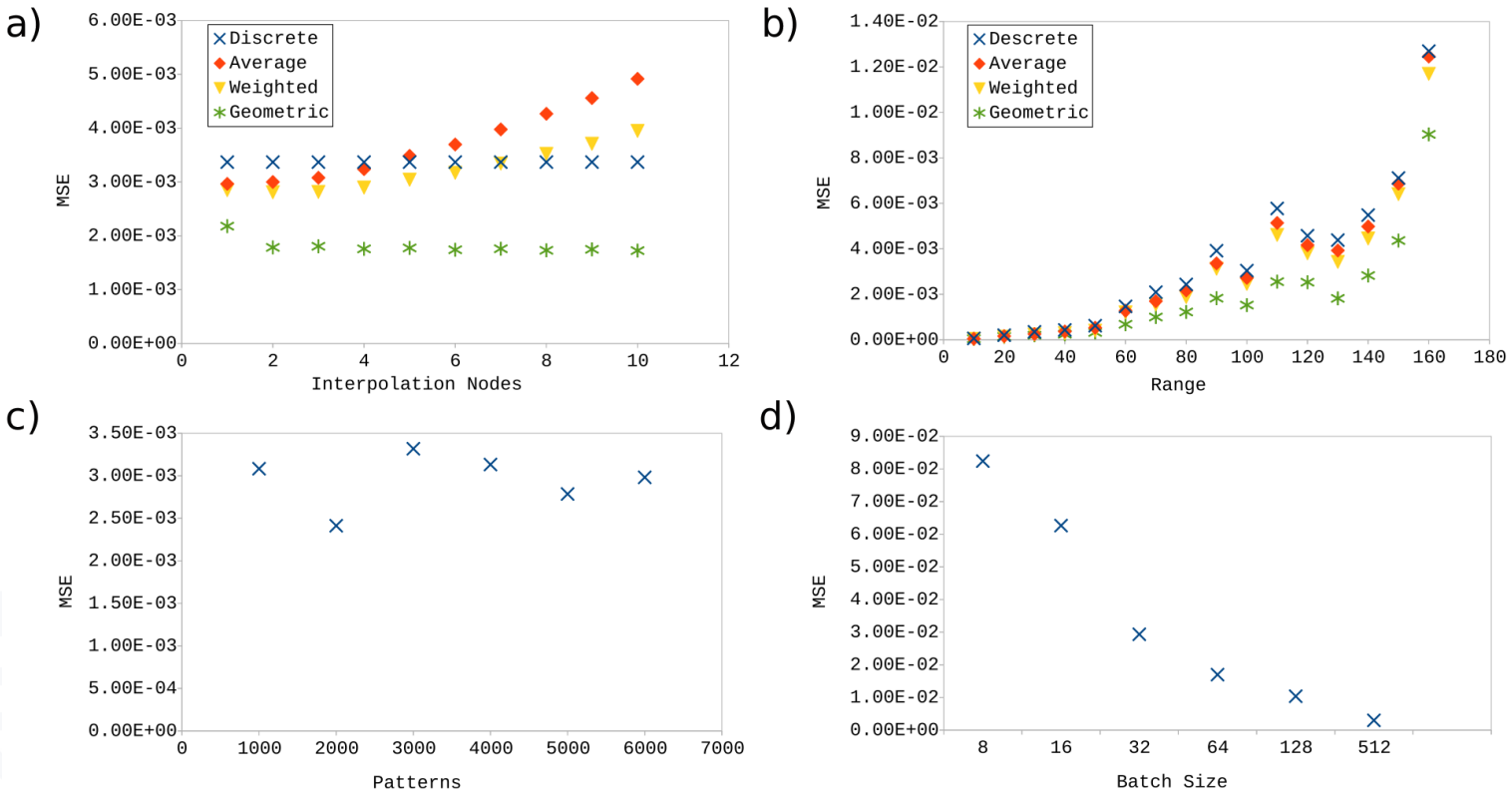
Continuous Self Organising Map

- Structure
  - 4 input nodes, 25^2 output nodes
- Training
  - Batch SOM training
  - Linear neighbourhood decay
- Use Phase
  - Euclidean distance for closest node(s)
  - **Interpolation**
    - Average
    - Weight average
    - Geometric

Aims of this work

- Utilise machine learning techniques to model unit quaternion based joint constraint
  - No Gimbal lock & single representation
  - Learn from patient/character data
  - Self Organising Map
    - Used to implicitly model boundary
      - Current orientation (unit quaternion) presented
      - Network responds with an interpolated output between the closest n winning nodes
- Simplified boundary

Results



- 1-2 required for improvement
- Geometric interpolation superior
- Improvement across the constraint range

Conclusions and Future Work

- SOM can provide nearest valid orientation in response to invalid input orientation
  - No decomposition/pre-processing of the quaternion required
  - Minimal normalisation of the output required
  - Can be trained from recorded (patient/actor) data
  - Interpolation with 1-2 nodes improves result
- Future work
  - Comparison to other approaches
  - Ability to learn more complex boundaries (irregular)
  - Rotation around the limb (twist)
  - Learning from motion capture data