Synthesis of Character Behavior by Dynamic Interaction of 'Synergies' Learned from MoCap data

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Computer Animation

Synthesizing of natural looking movements and reactive behavior in real-time is still an important problem.

1. Kinematic models driven by motion capture

   (e.g. Gleicher, 1989; Bodenheimer and Rose, 1997; Arikan et al.; 2003, Safanova et al., 2004)

   + high degree of realism
   − postprocessing is time consuming, much expertise is required, offline

2. Physical models for reactive behavior

   (e.g. Hodgins et al., 1995; Grzeszczuk et al.; 1998; Shao et al., 2005)

   + self-organized character behavior in real-time
   − often lacking rich details and simplified movements

3. Combination of the two approaches (e.g. Hsu et al.; 2005, Chai & Hodgins, 2005)

   ⇒ Possibility to synthesize a realistic animation in real-time
   ⇒ Complex dynamic systems

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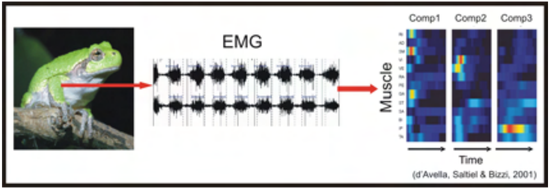
The Idea of Synergies

Motor Control

- Classical idea in motor control: Decomposition in low-dimensional control units with few DOF ⇒ **Synergies** (e.g. Bernstein, 1967; Flash & Hochner, 2005)
- Extraction of movement primitives from EMG data using unsupervised learning methods like PCA, ICA (e.g. d'Avella et al., 2003; Ivanenko et al., 2005)



⇒ Few movement primitives sufficient to generate different movements

The concept of movement primitives can be transferred to computer animation!

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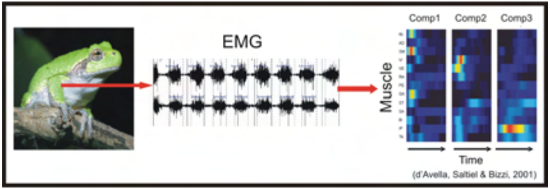

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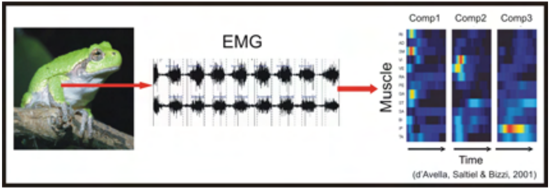

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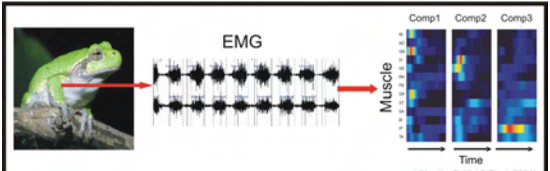

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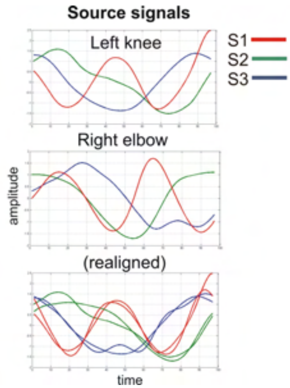
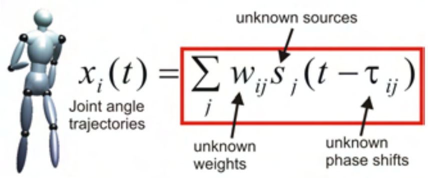
Main Goals

- Learning of movement primitives from full-body MoCap data
- Transformation of such trajectory models into a real-time capable animation system
- High-quality animation of complex human movements
- Interactive behavior and crowd animation

Learning of Movement Primitives

- **Motion Capturing** of natural, emotional straight and cyclic walking
- **Extraction of primitives** by using ICA on full-body joint angles
  $\Rightarrow$ Source signals very similar, but time-shifted against each other
- **Generative mixing model:** Superposition of independent shift-invariant source signals





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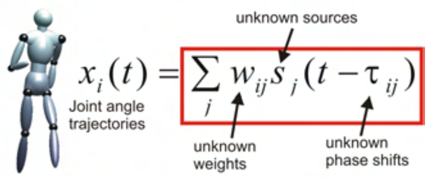

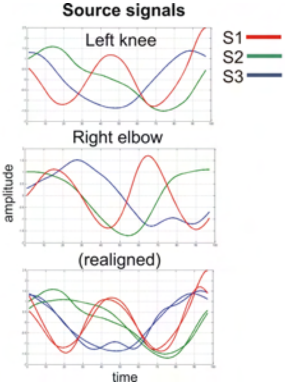

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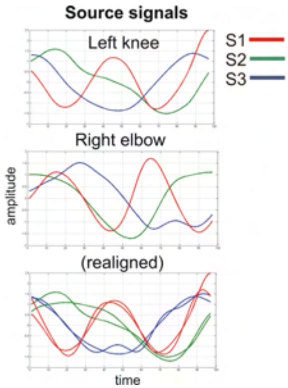

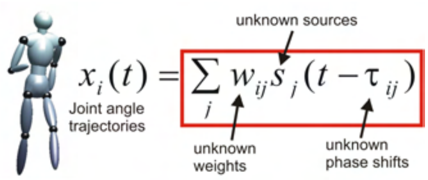

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New Blind Source Separation Algorithm

New algorithm based on Wigner-Ville transformation. (Omlor & Giese, NIPS 2006)

Mixing model to solve:

$$x_i(t) = \sum_j w_{ij} s_j(t - \tau_{ij})$$

Wigner transformation

time frequency

$$Wx_i(\eta, \omega) = \sum_j w_{ij}^2 Ws_j(\eta - \tau_{ij}, \omega)$$

Projection onto lower dim. spaces

$$\int \ldots\ldots d\eta, \quad \int \ldots\ldots \eta \, d\eta$$

(1) $$|\tilde{x}_i(\omega)|^2 = \sum_j |w_{ij}|^2 |\tilde{s}_j(\omega)|^2$$

Amplitudes of sources and weights estimated by **positive ICA**.

(2) $$|\tilde{x}_i(\omega)|^2 \frac{\partial}{\partial \omega} \arg\{\tilde{x}_i(\omega)\} = \sum_n |w_{ij}|^2 |\tilde{s}_j(\omega)|^2 \left[\frac{\partial}{\partial \omega} \arg\{\tilde{s}_j(\omega)\} + \tau_{ij} \right]$$

Phases of source signals and delays recovered

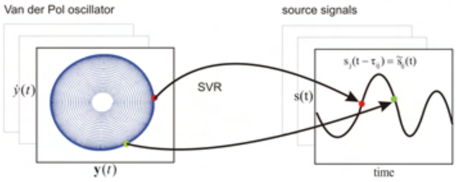
→ Sources, linear weights and the phase shifts

Approximation Quality

original | new algorithm 3 sources | PCA 6 sources

Real-Time System

- Source signals are periodic $\Rightarrow$ desired behavior must be driven by a stable solution of a nonlinear dynamical system: Van der Pol Oscillator
  $$\ddot{y}(t) + \underbrace{\lambda(y(t)^2 - k)}_{\text{Amplitude-dependent damping term}} \dot{y}(t) + \omega_0^2 \, y(t)$$
- Mapping is realized by nonlinear Support Vector Regression
  $s_j(t - \tau_{ij}) = \tilde{s}_{ij}(t) = f_{ij}(y_j(t), \dot{y}_j(t))$



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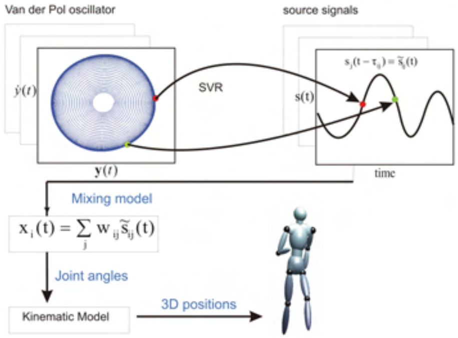

$\Rightarrow$ Generating trajectories by application of the mixing model

Stabilization by Dynamic Coupling

- Dynamic coupling between oscillators to stabilize coordination
- Form of coupling derived from Lohmiller & Slotine (2000) permits design of oscillator networks with a single stable solution
  $\Rightarrow$ Velocity coupling:

$$\ddot{y}_1 + \lambda\left(y_1^2 - k\right)\dot{y}_1 + \omega_0^2\, y_1 = \alpha\left(\dot{y}_2 - \dot{y}_1\right) + \alpha\left(\dot{y}_3 - \dot{y}_1\right)$$
$$\ddot{y}_2 + \lambda\left(y_2^2 - k\right)\dot{y}_2 + \omega_0^2\, y_2 = \alpha\left(\dot{y}_1 - \dot{y}_2\right) + \alpha\left(\dot{y}_3 - \dot{y}_2\right)$$
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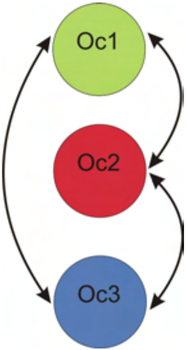

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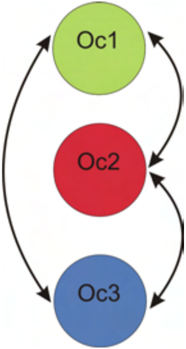

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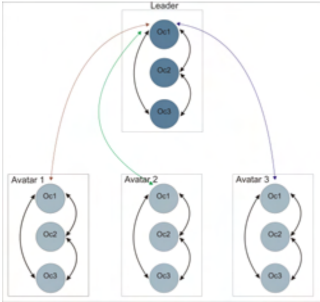
Coordinated Behavior of Crowds

- Dynamic coupling of multiple avatars

- Self-organized synchronized behavior
- Translation and rotation is computed from foot-ground contact events



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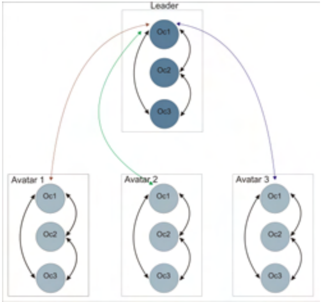

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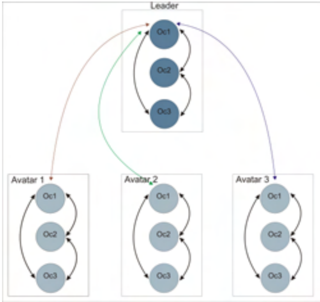

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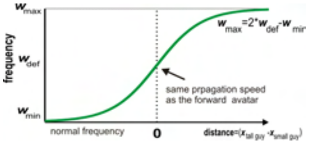
Interactive Behavior

Modulation of walking speed by change of the eigenfrequency ω_0 dependent on the distance $d(t)$ between characters

$$\omega_0(t) = f(d(t))$$



Example: Following behavior

Style Morphing

- Same sources and delays for all styles
- Styles (curved and emotional gaits) are defined by weight matrix

⇒ Style changes by blending weights using linear interpolation:

$$w_{ij}(t) = \mu(t)\, w_{ij}^{a} + (1 - \mu(t))\, w_{ij}^{b}$$

- Navigation as an example of style morphing:
  morphing weights μ depend on the change of heading direction φ_i

$$\mu(t) \sim \frac{d\varphi_i}{dt}$$

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Navigation Dynamics

For interactive behavior a navigation model is required

- Navigation dynamics from robotics (Schöner & Dose, 1995; Warren, 2006)
- The change of the heading direction is determined by the sum of three terms where $\mathbf{p}_i$ denotes the position of the character i:

$$d\varphi_i/dt = \underbrace{h^{\mathrm{goal}}\left(\varphi_i, \mathbf{p}_i, \mathbf{p}_i^{\mathrm{goal}}\right)}_{\text{goal-finding term}} + \underbrace{\sum_j h^{\mathrm{avoid}}\left(\varphi_i, \mathbf{p}_i, \mathbf{p}_j\right)}_{\text{instantaneous obstacle avoidance}} + \underbrace{\sum_j h^{\mathrm{pcoll}}\left(\varphi_i, \varphi_j, \mathbf{p}_i, \mathbf{p}_j\right)}_{\text{predictive obstacle avoidance}}$$

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Control of Walking Direction

1. **Goal-finding term:** (where $\varphi_i^{\mathrm{goal}}$ is goal direction angle of character i)
   $h^{\mathrm{goal}}\left(\varphi_i, \mathbf{p}_i, \mathbf{p}_i^{\mathrm{goal}}\right) = \sin(\varphi_i^{\mathrm{goal}} - \varphi_i)$
2. **Instantaneous obstacle avoidance:**
   $h^{\mathrm{avoid}}\left(\varphi_i, \mathbf{p}_i, \mathbf{p}_j\right) =$
   $\sin\left(\varphi_i - \varphi_{ij}\right) \cdot \exp\left(-\frac{(\varphi_{ij}-\varphi_i)^2}{2\sigma_\varphi^2}\right) \cdot \exp\left(-\frac{d_{ij}^2}{2\sigma_d^2}\right)$
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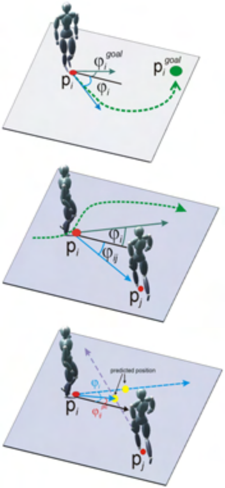

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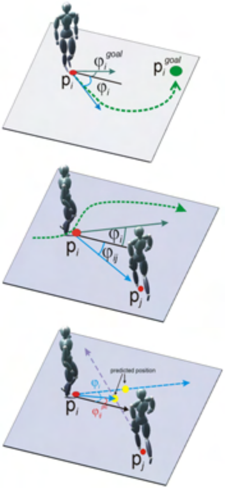

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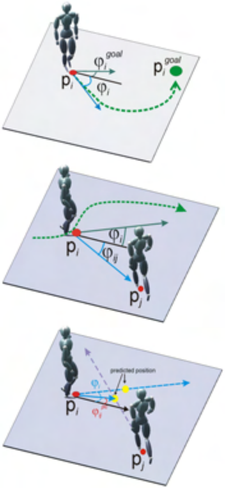
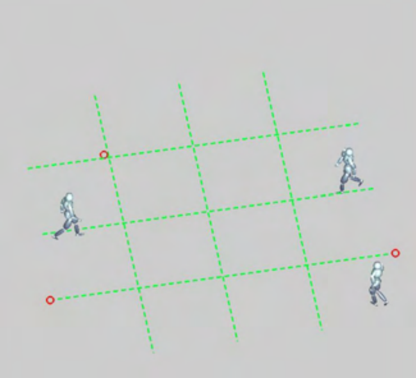
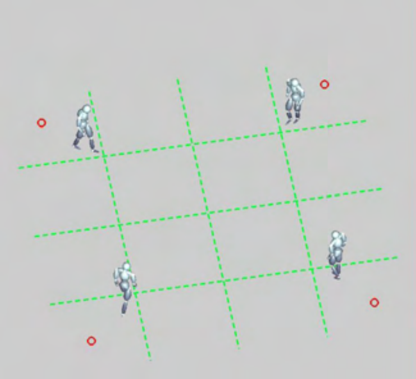


Navigation Demos

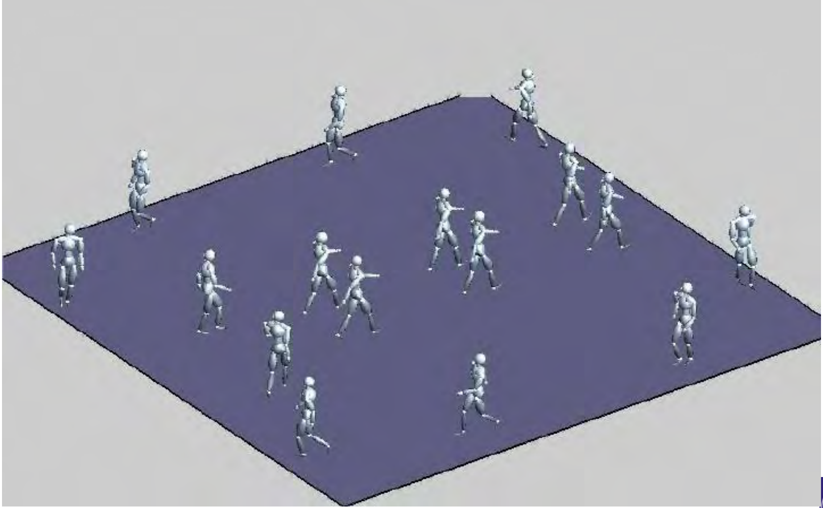
Navigation with emotional changes (from neutral to sad)



Navigation with emotional changes (from sad to happy)



Self-Organized Dancing Scenario of a 'Welsh Folk Dance'



Related work for synchron. dance perform. with music: (e.g. Takaaki Shiratori et al., 2006; Shinichiro Nakaoka et al., 2004)

Conclusion

- Simulation of realistic human movements based on learned components of MoCap trajectories, inspired by the concept of 'synergies'
- New more compact method of learning spatial components based on ICA with time-delays
- Real-time capable system: Mapping nonlinear dynamical systems onto the source signals using SVR
- Generating coordinated behavior by coupling dynamic primitives
- Navigation as an example for interactive behavior

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Conclusion

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