Robots that Learn: The Future of Man or the ‘Man of the Future’?

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A very interesting public lecture concerning conventional approaches to robotics, organised by the IET and presented at the Taros 2014 conference.
Below I have noted the time of sections which I found particularly interesting and relevant to PCT.

0.05.25 Claims that football robot can adapt to unseen scenarios.
0.07.00 Presents layout of what a robot needs to do for sensori-motor control, which includes planning, controller, plant, state estimator and sensory feedback.
0.09.45 States feedback is not sufficient for good control, that feed-forward predictive control is required. It is necessary to predict what forces are required for a movement, which is what humans do all the time, he says.
0.10.20 A feed-forward controller is a (predictive) model of the system (robot). Comprises a relationship between forces applied and what comes out.
0.10.35 Shows that a model of torques and angles of even a 2 degree of freedom arm is complex. Increasing the DOF to just 7, say, results in complexity grows exponentially.
0.11.00 Suggests that it would be better to use machine learning to acquire the relationships ‘on the fly’ by observing behaviour. Learn relationships between state of the system and the torques that need to be applied.
0.11.35 Use motor ‘babbling’ by moving robot at random or through some task then try to extract the relationships.
0.12.10 Torque (motor_i) = function (current_state, desired_state). This uses the (externally) observed state rather than the (internally) perceived state, methinks.
0.13.15 Set up is to clothe human in a high DOF sensuit and record positions and trajectories with computer vision motion tracking system.
0.14.30 Example of motor babbling to learn the ‘internal dynamics’ of a robot arm following a randomly moving target. Isn’t this just relating torques to a random disturbance?
0.16.00 Claims that this method can adapt to change in the physical properties of an inverted pendulum, though not clear if that is easy.
0.16.30 Provides what he claims is evidence that humans learn internal models. Though looks like someone learns to control in one way (with certain control parameters, gain etc) then has to learn to control in another way (with a different set of parameters); consistent with PCT re-organisation.
0.19.20 Shows the Justin robot which catches balls by detecting ball and predicting trajectory and using a path planner (running on an external cluster) to compute the optimal kinematics to catch the ball.
0.23.00 Example of motion capture and playback on robot. However, it is blindly going through the motions, open loop, without the ability to compensate for disturbances.
0.26.20 Demonstration of real-time motion capture and mimicking.
0.33.00 Talks about modelling the impedance (stiffness) characteristics of a hand, required for different situations.
0.39.40 Shows that higher stiffness is required for throwing a ball. Sounds like a good candidate for the setting of reference signals from memory for a specific task.
0.43.45 Prosthetic leg with specific stiffness settings. States that it is not able to modulate settings for different surfaces.
0.44.30 Goes on to describe a system where stiffness is modulated by sensing the type of surface. Sounds PCT-like, though adaptation with PCT due to errors arising due to change in surface, thus changing stiffness values.
0.46.00 Demo of ‘control’ of relationships, of robot hand with respect to box; though not sure how the control is achieved.
0.53.00 Talks about haptic feedback with prosthetic arm.
1.00.00 Quadcopters playing the James Bond theme music!