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Humanoid Motion Control using Auto Resonance Neural Network

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Abstract

It has been proven difficult to control robots with many mechanical joints due to a variety of problems, including redundant configurations, non-linear displacement, dynamic user surroundings, etc. Iterative computations have been applied to address inverse kinematic problems of industrial robots with up to six Degrees of Freedom (DoF). With one to three degrees of freedom in each of more than hundred joints used by humans for locomotion, the complexity is unfathomable. Consequently, in humanoid structures, algorithmic and heuristic approaches have failed. Numerous research fields that were earlier thought to be challenging to solve with computers have seen interest piqued by recent advancements in artificial intelligence and machine learning. One such domain is humanoid motion. This paper presents a novel kind of Artificial Neural Network named as Auto Resonance Neural Network (ARN). ARN uses the pull-relax mechanism applied by biological systems to control musculoskeletal motion. A variety of functions can be employed to build the pull-relax model, contingent on variables such as range, necessary coverage, and tunability. When employing ARN for joint control, inverse kinematics or some other kind of repetitive solution is not required. Its application is not influenced by the DoF or joint count. The network can use the learning methods like reinforcement learning or supervised or unsupervised learning.

Keywords: *Artificial Intelligence, Artificial Neural Network, Auto Resonance Neural Network, Deep Neural Network, Humanoid Motion Control, Machine Learning*

1.0 Introduction

Building a machine that works like a human being is a nightmare of mankind since the commencement of civilization. When the US Defense Advanced Research Projects Agency (DARPA) declared its goal to create a bipedal robot that could perform everyday tasks like getting into a car, it took a significant push to make this dream a reality[1]. This action through DARPA was brought forth in reaction to the terrible tsunami that struck the US-built nuclear reactors at Fukushima on March 11, 2011. If humanoids had been around to labor in the hazardous conditions of radioactive leaks in the initial days following the catastrophe, the harm it inflicted might not have been as great. It is a hard task to incorporate a biological system's flexibility into an electromechanical device, even with the impressive examples of Japanese industrial behemoths Honda and Sony's Asimo and QRio projects.

It is anticipated that a robotic humanoid will make judgments on its own without human operator guidance. The purpose of biological systems is not restricted to a pre-programmed sensory-control system. The action is controlled by temporal, cultural, environmental,

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emotional, and analytical factors. It is very hard to include all of these elements into an electro-mechanical system.

Three types of issues can be identified with humanoid systems:

- The acquisition, conversion, and abstraction of sensory data.
- Categorization, Absorption, and Comprehension.
- Regulation and Motion.

These are all complicated issues. It is known that few of these problems are NPHard. For instance, it is known that the Movers problem, which addresses the transference of a convex object in a limited channel, is Pspace-hard[2]. Though, expecting any sort of analytical solution- especially in closed loop form- is unrealistic, Artificial Intelligence (AI) and Machine Learning (ML) techniques are providing solutions to some of the problems. In this paper, a new type of Neural Network (NN) known as Auto Resonance Neural Network (ARN) applied to humanoid motion control is explained. If the robots and humanoids are developed using ARN, they can find applications where path detection is one of the criteria. Mining is one such field where automated robots that are built using hierarchical ARN can reduce the human effort and give the maximum throughput.

Robots/humanoids can be used for variety of applications space exploration, industries, agriculture, health care, mining and many more. Robots or humanoids that built using layered ARN can find applications where some kind of intelligence should be incorporated with robots and humanoids. Mining is one such field where automated robots which are built using hierarchical ARN can reduce the human effort and overcome hazardous problems including saving the human lives.

2.0 Literature

2.1 Humanoid Motion

The smallest level of human motion is produced by individual muscle motor units. Tendons link the joint segments to the motor units. Muscles act on joint segments in a predefined order to exert a certain force, which controls motion. While corresponding muscle relaxation permits constricting muscles to apply their full force to the joint segment, contraction of the muscles will pull the joint segment. Every single motion occurrence involves multiple joints, so the force exerted at the termination point needs to be divided between the linked joint segments. As a result, final location and joint locations, force distribution across the joints, and specific synchronization data are all included in a report of a motor action. When synthesizing commands for motor control, the Central Nervous System (CNS) may employ a special ordering system that assigns a higher priority to specific force distributions[3]. The CNS does not give every motor unit in a muscle the same action command. It has been noted that as the number of actuators is distributed in a variety of configurations, the cost of producing a movement decreases[3]. There will be more potential solutions if there are more actuators. Choosing contiguous sets from these solutions is necessary for contiguous motion utilizing such a huge number of solutions. Self-Organizing Maps (SOM), which resemble those of the CNS, can be trained using this selection process[4].

One can categorize joints as compliant or stiff. Even after the actuator has moved. The stiff joint and applied force, the joint remains locked. The joint will return to its zero-force position when force is removed. Walking robots, like the one in Figure 1, are made to have flexible joints, whereas industrial robots are made to be as rigid as possible.

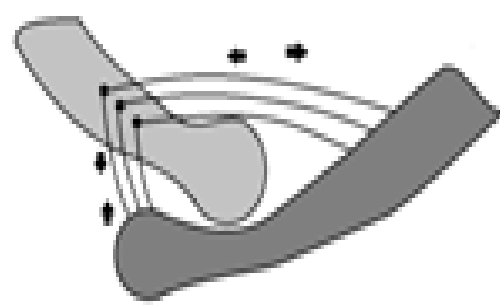

Figure 1. Typical arrangement of a biological joint.

Published studies on robotic control have used less number of Degrees of Freedom (DoF) and have been configuration-specific. For instance, 6-DoF arm designs have been documented in the literature[5]. The biological processes underlying joint motor control can be achieved using features such as U-control and their kinematic modeling[6]. Current demonstrations of humanoids have 25–40 DoF, whereas humanoids have 200 to 300 DoF.

The authors discovered that a humanoid is capable of both bipedal and quadrupedal movement[6]. This paper also presents the robot's kinematics. A humanoid design called CoMan, is shared by Italian research teams[7]. From a sole non-compliant muscle to a compliant joint, the hierarchy changes. Like a biological joint system, a puller is an actuator that is primarily in charge of motion, while the follower keeps the tendon from becoming slack. This work's joint control design is based on a comparable pull-relax model.

The Euler-Lagrange invention or the Newton-Euler invention is applied to identify the analytical structure of a robot[5,6]. While the Newton-Euler model is based on Newtonian dynamics, the Euler-Lagrange structure is based on energy conservation equations. For joint systems that are serially connected, coordinate systems must be reoriented. Usually, Denavit-Hartenberg notation is applied to join these reference frames. Upon specification of the joint angles and exerted forces, the displacements are computed using forward kinematic equations. Joint angles and torques to a given end terminal are computed using inverse kinematic equations. The functions of joint angles and forces in these equations of motion are non-linear. Therefore, to solve such equations, iterative solutions must be applied. When a mechanism has a large DoF, the computational effort needed to solve such equations becomes prohibitive. Finding heuristic, neural, genetic, or other similar soft computing techniques is therefore necessary.

2.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are structured like biological neural systems and they are very different from traditional digital systems. Artificial Neural Networks has been applied to a variety of fields such as Natural Language Processing, control systems, and data classification. For electromechanical systems with low degrees of freedom, deterministic processes like the Newton-Euler formulation work well; soft computing techniques are more appropriate for humanoid movement[5].

Artificial Intelligence (AI) can now be combined into digital control systems due to recent growth in ANN technology. Benbrahim has implemented ANN-based reinforcement learning to walk on two feet. In pattern recognition tasks, multilayer feed forward and recurrent neural networks have shown promise. An outline of deep learning techniques is presented by Schmidhuber[4]. Deep learning has recently been commonly applied to robotic perception and control[5]. Radial Bias Functions (RBFs) have been employed by He, Zhang, and colleagues to train neural networks for planar robotic manipulators[6] that can operate in the existence of dead zones in a work space. A control system for robotic system with large DoF have to deal with huge search space. The "stability-plasticity dilemma" must therefore be solved by neural systems that can be applied in this way in order for learning to continue without affecting previously acquired knowledge.

3.0 Neural Network for Joints Motion Control

Iterative inverse kinematics techniques are typically used to offer solutions to joint motion control problems, involving the calculation of joint angles and force. For joints with few degrees of freedom, closed form analytical solutions are feasible. For 6-7 DoF, iterative solutions utilizing the Newton-Euler representation are frequently employed. Higher DoF joint systems is employed using neural and fuzzy systems. Deep neural networks seem to hold the promise of providing generalized solutions for joint systems with high degrees of freedom.

3.1 The Joint System

Moveable mass-spring-damper parts and a drive system make up a joint system. The joint system is moved by a number of hinged parts; each has a set degree of freedom. A spherical joint with three segments each having one DoF is used in this simulation work. A complex joint system can have several of these joints and segments added to it.

3.2 Neural Network for Motion Control

ARN is used as the input classifier in a multi-layer neural network that is implemented for motion control. The objective is to navigate the joint system's end effecter from its present location to a terminal location by way of a number of nodes that are situated along a nearly ideal path while dodging impediments along the way. Higher levels offer motion paths and control structures for path optimization.

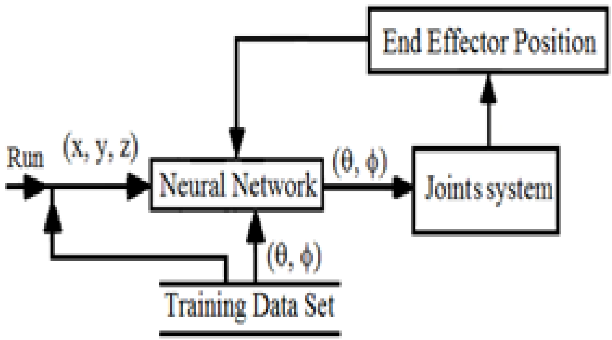

Figure 2. Overview of the joints control system using ARN.

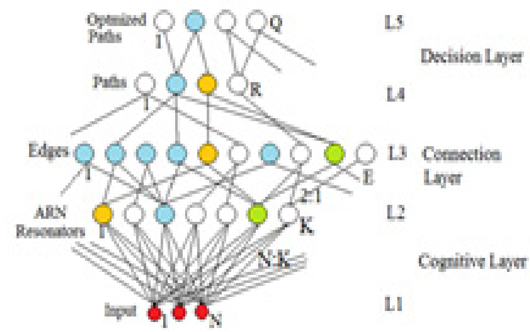

Figure 3. Hierarchical/Layered ARN for joints motion control.

An outline of the neural network-based multi-layered joint control system is presented in Figure 2. The mechanical design provides a well-defined 3-D work area for the multi-segmented joints system. The system learns without supervision. The end-point is found and the joints are randomly stimulated during the training. Strengthening When learning is applied in a typical application, the objective is to move the endpoint sequentially to a given location or collection of locations. The network gains the ability to associate the location of the end point with a set of joint angles $\{\{x, y, z\}, \{\theta_1, \phi_1, \theta_2, \phi_2, \ldots\}\}$ during training. While the second part is retained in memory by the node, the first part serves as a prerequisite for resonance.

3.3 Hierarchical ARN

A novel architecture, the ARN, is proposed to partially resolve the plasticity- stability problem. It is built using the fundamental principle of adaptive resonance. In this work, ARN models the pull-relax model of joint control using a radial bias function. The current work on ARN solves these issues and continues to expand over time[8].

Real time input categorization is possible with ARN. To implement functionality specific to an application, extra support infrastructure is needed. Such assistance can be given by a hierarchical network of nodes[9]. Figure 3 depicts one such potential motion control structure.

A hierarchical/layered network is constructed using ARN for robotic joint control. Finding a route through the ARN layer's nodes to get to the destination determines the robotic arm's actual motion. ARN is used in the first layer of the layered structure to classify received data and generate potential joint angles. Using a joining network at layer 2, a spatial alignment is superimposed on the first layer to aid in path finding. In layer 2, the first set of edges is made at random. These edges have weights that change based on how they are used. Additionally, connections can be made in runtime. At layer 3, the network has edges that can gradually direct the arm or the robot in the direction of the target. At each layer of the layered structure, different kinds of neural cells are used to carry out distinct tasks. As nodes are chosen one after the other and move towards the end point, joint angles are released sequentially. Higher layer cells within the network regulate this series of cell firings. In order to reduce the cost of motion, a further higher layer 5, chooses the best path from a variety of options.

4.0 Results and Discussions

The R programming language is used to simulate the ARN and the layered network. The outcomes demonstrate that this kind of network can solve an extensive range of problems related to humanoid motion control.

Robotic control must handle two primary phases of motion: The actual motion of the arm or robot itself, avoiding obstacles and minimizing a certain cost, and the computation of joint angle to reach the target location. Paths are dynamically searched. Reinforcement learning is the constant training process for hierarchical ARN. As a result, obstacles may be added while the program is running. The simulation results of a layered ARN that can find routes around obstacles are displayed in Figure 4. The

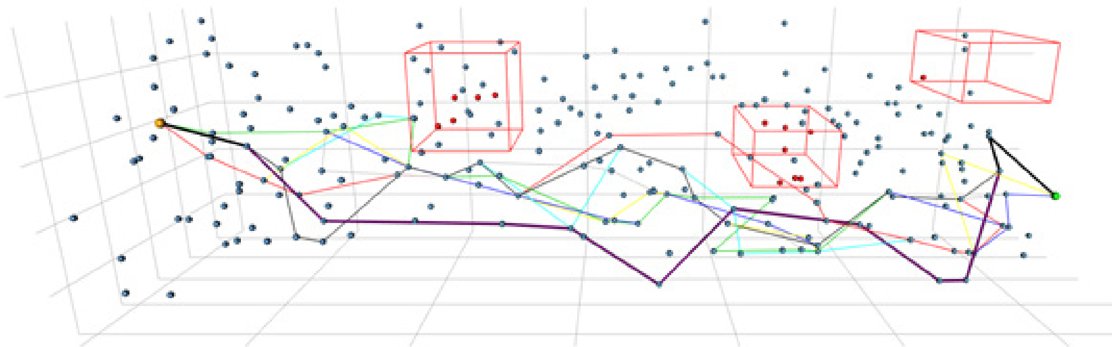

Figure 4. An optimized path for a three segment spherical joint with obstructions.

source is shown by an orange dot, and the destination by a green bubble. Red bubbles and blue bubbles represent the obstructed/blocked nodes and the free nodes respectively. Cubes represent the obstructed zone. Different colored lines represent the multiple paths. The path with the dense line indicates the best path among several paths and the best path has the smallest path length and minimum cost compared to other paths.

5.0 Conclusions

Using the pull-relax structure of the musculoskeletal system, the Auto Resonance Neural Network is a new artificial neural network structure for controlling humanoids' joints. A proposed layered neural network makes use of ARN. The pull-relax model of ARN is been applied to simulate joints using the network. Higher DoF joints is simulated using a Spherical (3D) joint with 3 DoF. When sparse input data is given to the network, it can learn from it. With gross granularity, the network synthesizes inserted nodes. Reinforcement learning improves these nodes' accuracy. The underlying ARN is given a spatial order by connection layers. Paths between nodes are established via this network. Sequential firing opens these pathways when the joint's end effecter needs to move. The network will determine a path if it exists. In order to lower a cost function, nodes at higher levels of the suggested structure also optimize the path and create new connections. The network can avoid blocked paths in order to reach the target.

Robots/humanoids can be used for variety of applications space exploration, industries, agriculture, health care, mining and many more. Robots or humanoids that built using layered ARN can find applications where some kind of intelligence should be incorporated with robots and humanoids. Mining is one such area that requires humanoids around to labor and handle the dangerous situations with some intelligence. Automated robots which are built using hierarchical ARN can be used in mining to reduce the human effort, to get maximum throughput and handle the work with some intelligence.

6.0 References

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