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Review Paper

ARTIFICIAL NEURAL NETWORKS IN ROBOTIC APPLICATIONS

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Abstract: There are a number of problems that their analytical solutions are difficult to obtain using conventional techniques in robotics. This paper examines the use of Artificial Neural Networks (ANNs) as a new technique to solve such problems in the field of robotics.

This paper presents an overview on ANNs applications to robot kinematics, dynamics, control, trajectory and task planning, and sensing. Moreover, the advantages and disadvantages of using and implementing ANNs to the robotic problems are outlined.

1. INTRODUCTION

The methodology of artificial neural networks (ANNs) was originally conceived as an attempt to model the brain of how to operate and function. The aim has been to create an artificial model which may be capable of emulating human intelligence. As a result of that ANNs have captured much more research interest and have been successfully applied to a wide range of application areas due to their adaptability and ability to learn, generalisation, fast real-time operation and easy implementation capabilities [1-5].

The aim in robotics is to create a device or a machine which can behave under human authority without representing any threat [6]. To reach this aim, it should be considered that the robots are highly nonlinear and complex systems and their dynamic performances depending on the efficiency of computing such tasks; co-ordinate transformation between the joint-variable space and the cartesian space, generalised forces/torques to drive the joint motors, the manipulator inertia matrix for model based control schemes, and the Jacobian matrix that relates the joint velocity in the joint-variable space to the cartesian space. These are the basic computations for the control of robot manipulators. Some of the intensive computations occur in calculating the robot kinematics, dynamics, Jacobian and their corresponding inverses. These basic robotic computations require better modelling for robust control. ANNs are known to handle such computations and tasks due to the capabilities.

In this paper, applications of ANNs are reviewed in the areas of robot kinematics, dynamics, control, trajectory and path planning, and sensing [1-148]. Firstly the problems in the area are explained. ANN solutions to those problems are then reviewed. Therefore, the advantages and disadvantages of using ANNs in robotics are summarised.

2. APPLICATIONS OF ANNS IN ROBOTICS

ANNs have presented great potential in many disciplinaries [3] as well as in robotics [7-10] because of the following features: generalisation through learning, fast computational capability for real-time applications, less priori information requirement and ease of implementation. ANNs have ability to provide plausible solutions for ill-posed problems in robotics.

The solution of robotic problems is difficult because even the simplest desired movement requires sophisticated mathematics which may require more computational effort. Common problems encountered in robotics are short intensive computations with high level of data dependency. These are major bottlenecks in the control of robots.

For robotic applications, the most popular ANNs are multilayer backpropagation and Hopfield network [11]. In addition, many other networks have been proposed which include competitive and co-operative nets [12], ART, Kohonen's Self-organising Map [13], Modified Counter-propagation, Functional net [14], Distributed Associative Memory [15], and an Learning Vector Quantisation (LVQ) network [148].

In the following subsections, the major problems in the robotics are first introduced. The applications of ANNs are then reviewed in each subsection.

2.1. Robot Kinematics

The term robot kinematics can be described as the study of robot joint motions without taking into account the causes of motion. It is classified into the inverse and the forward kinematics. The forward kinematics is a static geometrical problem of computing the location of the end-effector of a manipulator. The inverse kinematics calculates all possible sets of joint angles to attain the given position and orientation. The problems are computationally intensive and have multiple solutions. Various methods have been proposed to solve the inverse kinematics problem. They are the closed form solution, iterative methods [16], generalised inverse solution [17] and more recently ANN solutions [8-31].

Fig.1 depicts how ANNs may solve the inverse kinematics. An ANN is taught the relationship between the positions, x, y and z, and the joint angles, θ1, θ2 and θ3. A well-trained network is then able to provide the location of the end-effector for every possible solution.

ANN solutions of inverse kinematics for 2 and 3 degree of freedom manipulators can be calculated using multilayer perceptrons, Functional net, Backpropagation and Modified Counter-propagation net with Kohonen net, Cerebellar Model Articulation Controller (CMAC), Group Method of Data Handling, Hopfield net and co-operative/competitive ANNs [8-31].

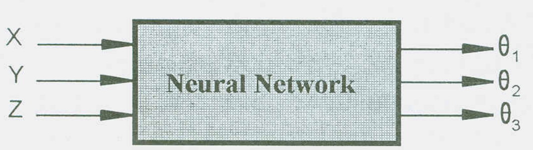

Figure 1. ANN solution for inverse kinematics

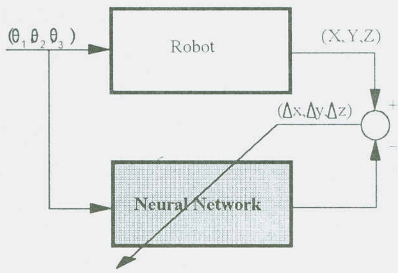

Figure 2. ANN solution for forward kinematics

Fig.2 shows how an ANN learns a forward kinematics. For the both kinematics, ANNs learn the robot function without requiring any priori information of the manipulator. After training, the networks may provide the desired position and orientation or all possible set of joint angels of the end-effector.

Learning, generalisation, the capability of fast real-time operations after an off-line training, requiriment of less priori information and the computation time, no need for conventional serial programming, and reducing the mathematical complexity are the advantages of ANNs for robot kinematics.

2.2. Robot Dynamics

Robot dynamics formulates the mapping between joint torques applied to the robot and the joint co-ordinates, velocities and accelerations. Because of mathematical formulations e.g. the Lagrange-Euler and Newton-Euler, a large number of trigonometric and non-linear functions of joint co-ordinates, velocities and accelerations are required. The non-linear mapping ability or function approximation of ANNs is attractive for robot dynamics. ANNs learn the behaviour of an inverse dynamics through a robot dynamics (it is very similar to the calculation of the forward kinematics as shown in Fig.2.). ANN is then used as an inverse dynamics controller.

ANNs are used to identify linear and nonlinear dynamic systems [32-40]. Recent reviews provided by [33-35] show how robots learn mapping of the inverse dynamics. ANNs are also used for the modelling of inertial sensor [36,37], for the inverse dynamics control for a PUMA 260 manipulator [41,42], to compensate for dynamic effects on the first two joints of the CMU Direct-Drive Arm II for a family of pick-and-place trajectories [42], for the flexible-joint manipulators dynamics and nonlinear characteristics [43], a real-time identification of a 2-D robot manipulator [44], and the identification of robot dynamics [134-141].

2.3. Robot Control

The basic objective of a controller is to provide appropriate input parameters to a robot in order to obtain the desired output. A controller has to provide a set of control parameters allowing the robot to reach a given target and must therefore know the parameters of the system for an optimal control. There are a number of situations that make the control difficult such as when a model of the system is not available, the system may change with time, or the controller itself may change with time due to component failures.

Use of neural networks in robot control offers a new promising direction for solving some of the most difficult control problems. ANN approach upgrades classic non-adaptive and adaptive control algorithms with acceptable performance characteristics over a very wide range of uncertainty [45]. Many of ANN applications to robotics have been performed in control because of their facinating features. Recent overviews present several learning control techniques and architectures for training neural controllers to provide an appropriate input to systems [33-35,46,47]. Bavarian [46] demonstrated several examples, especially, in situations where input was noisy or incomplete, an ANN was still able to produce reasonable results.

ANN learning algorithms accomplish an internal model of inverse robot dynamics during execution of movement and recognise changes in environmental conditions and react to them as required [48-50]. The use of ANNs in controlling robot manipulators and the power grasp robots [18,50-54,57,58], the Stanford-like robot [55], space robot [56], on-line the multi-joint robot manipulator [59] were successfully introduced.

Neurocontrollers are an existing new technology to the adaptive control of robots. Their ability to learn a control algorithm without the benefit of a priori analysis or modelling may be great benefit for difficult, complex, and non-linear robotic applications where either analysis, simulation, modelling, and identification are to expensive or not practical, or real-time operation is slow. The potential applications of neurocontroller are vast, and truly important to the long-term future. The techniques are already available to provide that potential [60-63].

The other papers on the applications are; the feedback loop and the inverse dynamics model for learning trajectory control of an industrial robotic manipulator [40], for general robotic control and a computed torque controller [64,65], one dimensional pole-balancing problem [19] by reinforcement learning [66], the control of the tracking behaviour of an autonomous mobile robot [67,68], three different neural architectures examined by [45] for nonlinear robotic control, the inverse Jacobian control with a hierarchical neural networks

[26,69], the structured hierarchical neural network [59] for the real-time control of mobile robots, the design and control multi-degree-of-freedom articulated robot hands [50,70-74], generating suitable grasp modes for various robot hands and for various objects [72], a gripper with three straight fingers [73], control of a robot arm and gripper for the task of grasping a cylinder [71], a recentralised variable structure control system [74], servo controller [70] for one or two dimensional robotic manipulators, direct transition from sensor processing to inverse dynamics [75], controlling the position of robot manipulator [76], guiding the end of the manipulator by CMAC [77], a mobile robot [78] for multi-tasks, underwater robotic vehicles [79-82] for increasing the autonomy of the vehicle control, recovering the image, teaching the pitch attitude of underwater telerobot with the combination of ANN and fuzzy logic, the neural compensation techniques by [83] for robot control, several ways for an existing controller development, direct adaptive control, optimised non-linear controller development [33,54,84], for time-optimal control [85], intelligent control [86], force control [121], the rule-based robot systems with ANNs [87-89].

The major advantages of ANNs with the use the of hybrid structure of several networks for robot control are : robustness to noise, error and damage; learning and adaptation; nonlinear analog processing; modelling and controlling unknown or uncertain systems.

2.4. Trajectory and Task Planning

In order to move a manipulator from one position to another in a smooth controlled fashion, each joint must change its location as specified by a smooth function of time. Trajectory planning is a process of specifying the desired trajectory in joints Cartesian space for joints or grippers. It is further complicated when the robot must move around obstacles or is constrained to the given trajectory. The problems involve the co-ordination of multiple sources of data and require problem solving techniques operating in a changing and harsh environment.

The applications to this area are; motion planning and learning control of a biped locomotive robot [90], trajectory formation [91], classification of robot hand grips [92], storing and retrieving trajectories [93], mobile robot path planning [94,95] for multi-joint robots and truss structures [96], robot manipulators [97,101], a map-based symbolic reasoning to achieve high-level behaviours [98], a real-time robot navigation system based on three VLSI neural networks [99], and a new control architecture for a specified trajectory [100].

Learning and generalisation abilities for robot nonlinearities, optimising the trajectories in task and trajectory planning, fast on-line operation and adaptability can be counted as their advantages.

2.5. Sensing

Sensing is an important area in robotics for any movement and control. Sensing devices are the only way of providing information about their environments. There are many different types of sensors available for robots, namely; tactile, speed, stress, acceleration, movement and position, inertial, visual, proximity, and optical sensors. The problems in sensing come from the environmental effects, temperature, noise, lack of light, fumes, humidity and components failures. A variety of materials, devices and sensing principles have been reviewed [102,103] for robotics. There are some application covers two areas [104,105]. The applications in tactile and non-tactile sensing will be surveyed in the following subsection.

2.5.1. Tactile sensing

Tactile sensing is important for intelligent robots. Unlike vision sensing it constrains the interpretation process due to loss of depth information in the image formation process, and provides absolute information such as local shape information, object's roughness or hardness to the robot manipulators.

Using a Hopfield network to recover surface stresses from strain data taken from a tactile sensor [106,107], a modular arrangement of MLPs trained by the BP algorithm to process data obtained from a tactile sensor to determine the shape of an object [108], an MLP (again trained by the BP algorithm) with a tactile sensor array to detect the angle of contact between a rod and a cylindrical finger of a robot hand [109], controlling a prosthetic hand [110], converting sensory inputs from the prosthetic hand into the appropriate nerve signals [99] for the patient in sensing and controlling the prosthetic hand directly, calibrating a 2-D displacement sensor [111], two BP-trained MLPs and a skin-like tactile sensor to compute the normal and shear stresses on the sensor and deduce the shape and radius of a surface in contact with it for grasping and manipulation tasks [112], an ultrasonic sensor for location determination [113], and an inertial sensor for location determination of an object on a platform [115,142], a BP-trained MLP to sense and control the grasping force of a robot hand [52], an MLP trained by the BP algorithm with a contact sensor to recognise and classify the geometry and roughness of various metal patterns [146], a BP-trained MLP with a force sensor to detect the state of contact between a cylindrical peg and a cylindrical hole during insertion of the former into the latter [147] are the selected applications.

2.5.2. Non-tactile sensing

Most of the applications of ANNs in non-tactile sensing can be found in vision system. ANNs are used to learn the non-linear mapping between image data and control signal for changes in the joint angles required to achieve the desired position and orientation using a vision system to position and orientate the end-effector (Fig.3). There are two ways of mounting cameras. In the first way, a camera is fixed at the end of robot manipulator. In the second way one or more cameras are mounted one or more places. The camera/s are directed to a working place and provide information about the motion or the object/s' location/s to be grasped and moved as shown in Fig. 4.

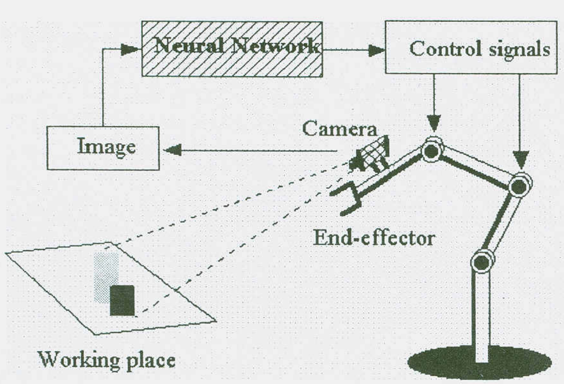

Figure 3. Visual control of a robot

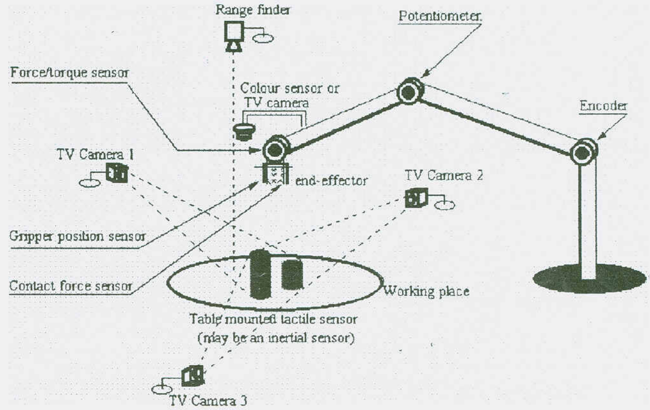

Figure 4. A multiple sensor system adapted from [104]

The visual information is processed and used to position and orientate the end effector of the manipulator from image data obtained from the working place through the camera/s [54,104,114-120]. Among the five human senses; vision, hearing and touch are meaningful to robots. Recently there has been increasing interest in upgrading robot intelligence by using multiple sensors as shown in Fig.3. [104,106]. In the figure, for a specific task, cameras provide locational information about the objects. The colour camera helps selecting a particular object depending on the object's colour. The range finder gives detail about the object shape and its range. Contact force sensor illustrates the forces on the contacts and so on so worth.

There have been several applications of ANNs to non-tactile sensing. They have mainly concerned visual sensing, although some ultrasonic sensing applications have been reported. The following are examples found in the literature:- Integrating the visual data into the control process without calculating an inverse kinematic of a manipulator [54]; Using two CMAC ANNs to learn the non-linear mapping between image data from a vision system and control signals to change the joint angles of a robot arm, in order to position and orientate the arm's end effector [114]. Similar work has also been described by [106] who have used two ANNs trained by the BP algorithm; Using machine vision systems for automated industrial inspection [116,117,121], Employing a vector-quantization network trained with Widrow-Hoff's delta rule to process visual information from two cameras thus enabling a robot to learn the position of its end effector [118]; Using a BP-trained MLP with a vision system for robotic (automated) inspection of wood [120] and automotive components [148]. In their work, a MLP and K-nearest neighbour classifiers were compared [120] and the former to have a slightly better performance were found. The MLP against an LVQ network were also evaluated and concluded in favour of the MLP [148]; Employing a supervised neural network to process stereo images from two cameras to enable sensory-motor coordination of a robot arm in grasping objects. The robot could adapt unforeseen shapes in the positions, shapes and sizes of objects [122]; Using a Kohonen self-organising map, with a vision system for bin-picking (acquiring objects from a storage bin). The system could handle noisy and distorted images and partially occluded and overlapping objects [15]; Using a combination of an MLP made up of three sub-networks with a vision system to recognise objects and determine their location [123]; Using a Hopfield network [124] and MLPs [126,127] with ultrasonic sensors to recognise objects; Learning a variety of actuators, dampers, adaptive structures, and active materials such those equal and opposite vibration wave forms [125]; Using colour image processing [128,133].

3. DISCUSSION AND ANALYSIS

As mentioned and explained in the previous sections, ANNs enable many important advantages to robotic applications. Use of ANNs in robotic applications is very fascinating from both scientific and technological point of view. Indeed, for certain problems ANNs might be likely to become a new technique. ANN learning algorithms in robot dynamics modelling, robot kinematics, robot sensing, robot control and, trajectory and path planning are some of the successful areas.

Although neural networks provide better solutions for most of the robotic problems effectively, it is needed understanding the principle of ANNs deeply. Using more integration of ANNs with other artificial intelligence techniques (fuzzy logic, genetic algorithms, expert systems, tabu search), investigate new neural network structures or architectures which may provide more precise solutions for more complex robotic problems. Some of the recent integration have been presented by [38,80,98,115,129,130,142,143]

In spite of being successful in solving robotic problems, ANNs have some drawbacks in the area like setting the network parameters, finding convenient structure or/and learning algorithms. The problems can be summarised as:- type of network to be used, learning algorithms, topology, number of layers, number of nodes, type of nonlinearities (sigmoid, sine), network parameters (seed, momentum and learning coefficients, initialisation), and the initial values of the weights and biases.

However, in order to train the weights of ANNs, the preparation of training data set takes an important part and the training procedure must be specified in considering the following points:- random training is inappropriate for on-line training; training set must be specified to give an adequate representation of the type of inputs.

The learning algorithm is an important factor for speed up the training and guarantee convergence. As summuraised above to find an appropriate network is not easy job, but the problems in the robotics solved by the use of ANNs guide the applicants in their research.

The following features make the ANNs more attractive for robotic applications :- Adaptability and ability to learn [26,30,32,37,39,41,42,131], fast real-time applicability [9,41,59,132], generalisation [21,22,24], tolerance to noise in the input information [67], less priori knowledge required [26,39,40,131], ease of integrating with other Artificial Intelligence techniques such as Fuzzy logic, Expert Systems and Tabu search [70,79,80,88, 89,98,129,142,143], and using several networks [71,115,134-141].

Altough the above properties make ANNs applicable to tackle most of the robotic problems, ANNs in robotics have also some drawbacks which may be encountered in some applications. These are:- slow to convergence during training, need large input data set for complex systems, lack of accuracyfor some applications, difficulty in choosing parameters and structure for different types of ANNs.

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