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Zhu, Qiuming and Tawfik, Ahmed Y., "Quantitative object motion prediction by an ART2 and Madaline combined neural network: Concepts and experiments" (1995). *Computer Science Faculty Publications*. 36.
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Quantitative object motion prediction by an ART2 and Madaline combined neural network

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Abstract. An ART2 and a Madaline combined neural network is applied to predicting object motions in dynamic environments. The ART2 network extracts a set of coherent patterns of the object motion by its self-organizing and unsupervised learning features. The identified patterns are directed to the Madaline network to generate a quantitative prediction of the future motion states. The method does not require any presumption of the mathematical models, and is applicable to a variety of situations..

1. Introduction

The problem of predicting object motions in dynamic environments is a concern to many researchers in computer vision and robotics. For example, a cooperative mobile robot must find the future moving positions of the objects (maybe the other robots) in its operating space, so as to avoid collisions with each other [1]. The object motion prediction is generally a problem with a high degree of uncertainty because of the unknown dynamics of the objects encountered.

Mathematical models were studied for describing, analyzing, and estimating the underlying characteristics of the object motions. A linear model took a weighted sum of the previous motion states to predict the future motions. Iterative algorithms were utilized to find the least-square-error solutions for the model [2]. A hidden Markov model viewed the object motion as a stochastic process and used state transition functions to predict the future states [1]. However, these models are often not justifiable to many complex situations in real world.

Using artificial neural networks to predict the object motions was studied by Tawfik et al. [3]. Elsner and the others [4, 5, 6] have studied the use of artificial neural networks to predict time series, a problem very close to the motion prediction. A back propagation network was used by Gent [5] for the prediction of both deterministic and stochastic time series. Sorheim utilized an ART2 and back propagation combined network for the estimation of dynamic processes [6]. However, the slow speed of

the back-propagation learning makes the networks not suitable to the motion prediction which requires a timely adaptation to abrupt and irregular changes of the object motion.

By an analysis of many object motion profiles, we found that an object motion sequence can always be divided into a series of smaller segments. These segments fall into a limited number of categories. We call each of these categories an Elemental Motion Pattern (EMP). Relating each EMP to a motion segment, the entire motion sequence of an object can be described by a series of distinct motion functions. Based on this observation, an ART2 and Madaline combined neural network was utilized in our research. The ART2 network autonomously classifies the sequences of motion states into the EMPs with certain levels of coarseness. It also suppresses certain levels of input noises and provides a qualitative justification for the underlying characteristics of the object motions. The Madaline network generates quantitative predictions of the object motion states with respect to the EMPs identified by the ART2 network. The combined network differs from the Sorheim's in that: (1) a simple one-layered Madaline network is applied, rather than the back propagation, for achieving faster responses to the motion variations, (2) a learning operation is conducted in every cycle of the prediction, rather than as a separate process, for improving the accuracy of prediction incrementally.

2. Modeling

Let $X(k)$ denote a segment of object motion profile, $X(k) = [x(k), x(k-1), \dots, x(k-n)]$, where n is a constant. Let $Y(k+1) = [y(k+1), y(k+2), \dots, y(k+m)]$ be the prediction of $X(k+1) = [x(k+1), x(k+2), \dots, x(k+m)]$. The component of $Y(k+1)$ can be expressed as $y(k+1) = x(k+1) + e(k+1)$. The objective of motion prediction is to obtain a $Y(k+1)$ such that

$$\sum_{i=1}^m e^2(k+i) \quad (1)$$

be minimized.

The $X(k)$ signal is stored in a push-forward shift register and fed to the ART2 and Madaline networks simultaneously. The connections of the two networks and the inputs/outputs are shown in figure 1. When a prediction process starts, two successive stages, a bottom-up and a top-down, take place between the $F1$ and $F2$ nodes of the attentional subsystem of the ART2 network [7]. In the bottom-up stage, sufficiently activated (by $X(k)$) $F1$ nodes emit bottom-up signals to the $F2$ nodes. The pathways between the $F1$ and $F2$ nodes multiply the signals with the connecting weights. The multiplied signals lead to a competitive activation among the $F2$ nodes. Each $F2$ node is associated with a specific EMP. Let the $F2$ output be denoted as $Y = (y_1, y_2, \dots, y_d)$, where only one y_i should have a non zero value which marks the winner of the competition. This winner node signifies the identification of a specific EMP in the motion input. The Y is fed back to the $F1$ layer in the top-down stage by passing through the connecting weights. Three streams of data flow to the $F1$ nodes in this stage. They are (i) the bottom-up input, $X(k)$, (ii) the top-down input, Y , and (iii) a gain control signal, G , generated internally. The G switches the network among the states of (i) pattern generation, (ii) pattern matching, and (iii) network adjustment. An orienting subsystem of ART2 is responsible for sensing mismatches between the bottom-up and top-down signals. A sufficient mismatch results in a reset, which makes the current winning $F2$ node ineligible in further competition. The network enters into a stable state when no disagreement between the $F1$ and $F2$ activation is found.

The activations developed in the $F1$ and $F2$ nodes are called short-term memory (STM) traces. The STM traces exist only in association with a single application of an input. The weights associated with the bottom-up and top-down connections between the $F1$ and $F2$ nodes are called long term memory

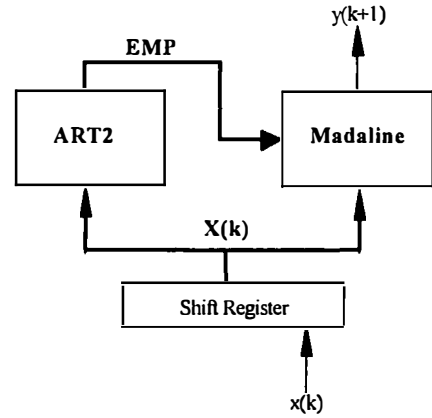


Fig. 1. Data flow within the combined net for object motion prediction.

(LTM) traces. The LTM traces actually encode the EMP patterns that remain a part of the network for an extended period. The EMPs are generated in the ART2 in an autonomous fashion. When no existing EMP sufficiently matches the current input, a new neuron node is added to the $F2$ layer, plus the connections to the $F1$ and other $F2$ nodes. When an $X(k)$ matches with an existing EMP, the network generates an activation Y at the $F2$ layer almost immediately. In this way, the network responds quickly to previously learned patterns, meanwhile remaining able to learn novel patterns. When the network enters a stable state, i.e., a pattern matching occurs, learning takes place on the connections between the $F1$ nodes and the activated $F2$ node. After the weights are up-dated, all the nodes of the $F1$ and $F2$ layers are restored and ready to respond to a new $X(k)$.

Once an EMP is identified by the ART2 net, the activated $F2$ output is channeled to a one-layer Madaline network. The structure of a Madaline network can be viewed as a collection of Adalines [8]. Only one Adaline responds to the identified EMP by receiving an excitatory input from the activated $F2$ node. All other Adalines receive inhibitory inputs from the deactivated $F2$ nodes. Quantitative computation is made in the excited Adaline by taking an inner product of the $X(k)$ and the network weights. The output of the Adaline is gated by an analog OR circuit to produce the Madaline output $y(k+1)$. When a new EMP is generated by the ART2, a new Adaline is also added to the Madaline. Learning takes place at the excited Adaline when the signal $x(k+1)$ is received. The overall process of object motion prediction is thus conducted in two steps: (1) EMP identification by the ART2 network, and (2) quantitative $y(k+1)$ generation by the Madaline network.

3. Simulations

Computer simulation was conducted for evaluating the performance of the ART2 and Madaline combined network¹ for object motion prediction. Experiments were done on both artificially generated motion data and real object motion profiles. In the first case, a set of mathematical functions are used to generate the testing data. These functions facilitate the evaluation of the prediction errors. By changing the parameters of these functions, object motions with different characteristics of swiftness and abruptness are tested.

The mean-squared error (disparity), E_{MSE} , between the predicted states and the actual states of the object motions are computed. The simulation results of the combined network are compared to a feed forward network using a back propagation learning [6]². Table 1 lists the E_{MSE} values for the test cases, where cases $S1$ to $S4$ use artificially generated data and case AA uses actual object motion profile. It shows that the combined network improved the prediction precision over the back propagation network in all testing cases. The improvement is especially significant in the cases where the object motion exhibits strong irregular and swift variations.

An ART2 neural network can adapt to the environment changes by developing its own set of connection weights in computing the matches between the input signals and the outputs. This makes it very suitable for object motion predictions. Even though the feed-forward neural networks of today often have many layers, we believe that a

¹ The implementation details of the combined network is the following.

The ART2 network has the following parameters:

vigilance (ρ)	= 0.9
threshold (θ)	= 0.3
integrator step size (h)	= 0.1
max. number of integration steps	= 100
convergence criteria for dynamic activation	= 0.001
convergence criteria for the weights	= 0.01

The parameters of the Madaline are the following:

number of input neurons	= 8
number of output neurons	= 1
convergence criteria (ϵ)	= 0.01
momentum factor (α)	= 0.9

² The B-P network has the following parameters:

number of input neurons	= 8
number of output neurons	= 1
number of hidden neurons	= 8
learning rate (ϵ)	= 0.01
momentum factor (α)	= 0.9
convergence criteria (ϵ)	= 0.001
activation function	= linear

single layer Madaline network is appropriate to compromise the real time speed and the adaptive functioning requirements, especially when it is incorporated with the pattern recognition feature of the ART2 network.

Test cases	B-P Network	ART2- Madaline Network
$S1$	0.01958	0.00596
$S2$	0.096518	0.009593
$S3$	0.018583	0.009810
$S4$	0.85709	0.734878
AA	0.004204	0.003028

Table 1. E_{MSE} of the test cases.

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