Generator of unidirectional irregular wave with linear motor and supervised neural control

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Abstract. The coasts are affected mainly by the wave. The wave is a complex phenomenon and very important for the design of the structures that are used in the coastal zones and beaches. This paper presents a novel control system for the generation of unidirectional irregular waves, in project and research laboratories. The system uses digital signal processing, a feedforward neural network and a linear motor, as main elements. The research objective is to obtain a system of easy operation and greater efficiency. With the combined neural control, the transitory response disappears quickly. This behavior is interpreted, in marine hydraulics, as a fast calibration of experiments.

1 Introduction

The wave is a main element for to design coastal and maritime constructions [1], [2]. The phenomenon is very complex and its mathematical representation is difficult [3], [4], [5] [6], [7], [8], [9]. The mathematical models make possible to represent the sea disturbance and to calculate their effects, although in many cases, they need a calibration by means of physical modeling on reduced scale. In complex marine work designs, the physical modeling on reduced scale, is essential. This paper presents a system for the generation of spectral patterns of unidirectional irregular waves, in project and research laboratories. The system uses digital signal processing, a neural network and a linear motor, as main elements.

The research objective is to obtain a system of easy operation and greater efficiency with respect to traditional methods. The transitory response disappears quickly with the combined neural control [10], [11], [12]. This behavior is interpreted, in marine hydraulics, as a fast calibration. In addition, the spectral patterns of the generated wave will have small errors with respect to the spectral patterns of reference.

2 Technical Support and Schemes of Operation

Fig.1 presents the combined neural control for spectral patterns generation of irregular unidirectional wave, where:

S_T : Target spectrum; S_G : Generated spectrum.

The controlled process is a wave channel and the control final element is a generator formed by a linear motor and a paddle device (fig 2). A linear motor [13] is a type of electric motor; an induction motor in which the fixed stator and moving armature are straight and parallel to each other (rather than being circular and one inside the other as in an ordinary induction motor).

The maximum force offered by a linear motor is determined by its construction and is dependent on the position of the slider in the stator. The maximum force curve is symmetric to the centre of the movement range, the so-called Zero Position ZP. If the distance between the end of the stator and the end of the slider is equal to the Zero Position ZP of the motor, the slider is at the centre of its movement range. The Zero Position ZP can be found in the data sheet of each linear motor and is different for each motor. In the SS (shortened stroke) range, the slider's drive magnets are wholely inside the active part of the stator. This provides optimum force generation and a constant maximum force over the whole SS- stroke range. The more the slider moves away from the SS-stroke range, the fewer of its magnets are in the active part of the stator. This means that the maximum and effective forces are reduced linearly as the end of the stroke range S is approached.

A controller PI (proportional-integral) and an inverse neural network (INN) form the combined control.

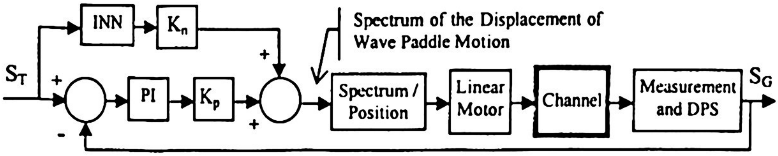

Fig. 1 Combined neural control for spectral patterns generation of irregular unidirectional wave

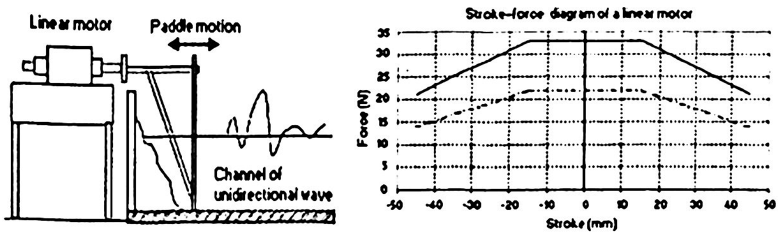

Fig. 2 Unidirectional wave channel and stroke–force diagram of a linear motor.

2.1 Supervised neurocontroller system design

The combined neural control also is called supervised neurocontroller and its general diagram is shown in Figure 3.

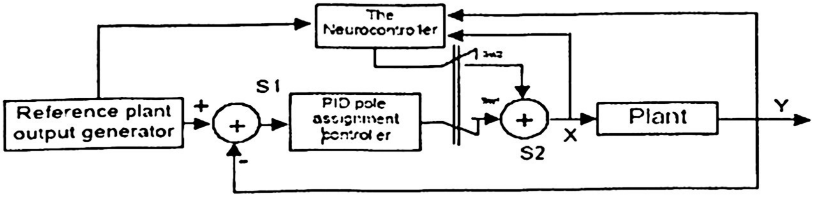

Fig. 3 Supervised neurocontroller system design.

The methodology of neurocontroller system design [15], [16] can be described briefly as learning of a neural network to act as a controller. The control signal generation by using the neurocontroller has the following steps:
1. Determining inverse model parameters which are used in control signal generation U_n which will be the output of this model under the effect of PID controller.
2. Learning of the neurocontroller to generate the control signal according to reference pattern which is obtained from the previous inverse model.
3. Learning the network until the RMS value come to the lowest value as far as possible (to minimize the resultant error).
4. Applying the control signal, generated from the neurocontroller, to the system.
5. Using the output of the system as a feedback input of the neurocontroller to generate the following control signal.
6. Repeating the above steps until the end of patterns.

3 Wave Generation Theory

Eq. (1) is basic for the spectral analysis of a registry of irregular wave in a fixed station, and this defines the function of spectral density *S(f)* [2].

$$\sum_{f}^{f+df} \frac{1}{2} a_n^2 = S(f)df \tag{1}$$

This equation, nevertheless, contains an infinite number of amplitudes a_n of components of the waves, and this is not applicable to practical calculation. For the practical analysis, a wave registry of N points is acquired, with a constant sampling period: $\eta(\Delta t)$, $\eta(2\Delta t)$,...$\eta(N\Delta t)$. The analysis of harmonics of wave profile $\eta(t)$, the profile can be expressed as the well-known finite Fourier series [2], [18], Eq. (2)

$$\eta(t) = \frac{A_0}{2} + \sum_{k=1}^{N/2-1} (A_k \cos(\frac{2\pi k}{N} t_\bullet) + B_k \sin(\frac{2\pi k}{N} t_\bullet)) + \frac{A_{N/2}}{2} \cos(\pi t_\bullet) \tag{2}$$

$$t_\bullet = t / \Delta t : t_\bullet = 1,2,3,...N$$

The wave power spectrum can be generated by two general methods: first, in discreet form, with a series of Fourier and the components of power of each one of the harmonics. The second, in the continuous form, with the significant wave height and period and empirical equations of spectrum such as the Mitsuyasu [2], [9], Pierson and Moskowitz JONSWAP [2], etc., for example, the spectra of wind waves fully developed in the open sea, can be approximated by the following standard formulas:

$$S(f) = 0.257 H_{1/3}^2 T_{1/3}^{-4} f^{-5} \exp[-1.03(T_{1/3} f)^{-4}] \tag{3}$$

$$S(f) = 0.205 H_{1/3}^2 T_{1/3}^{-4} f^{-5} \exp[-0.75(T_{1/3} f)^{-4}] \tag{4}$$

where $H_{1/3}$: significant wave height; $T_{1/3}$: significant wave period; f : the frequency.

Fig 4. presents an example of sea spectrum. The dash-dot line is the result of fitting Eq. (4) with the values of the significant wave height and period of the record. Although some difference is observed between the actual and standard spectra, partly because of the shallow water effect in the wave record, which was taken at the depth of 11m, the standard spectrum describes the features of the actual spectrum quite well.

The wave generator of mechanical type is more useful and simple and it reproduces better the waveforms. The theory of displacement of the beater (paddle) and the characteristics of the generated waves are studied by several investigators [2], [3], [4], [9]. The desired wave power spectrum is multiplied by the transfer function of the wave generator, well known as equation of efficiency of the paddle. This transfer function is obtained when solving the differential equation for the free boundary conditions (see Eq. 5 and 6)

Piston type:

$$F(f,h) = \frac{H}{2e} = \frac{4\sinh^2(2ph/L)}{4ph/L + \sinh(4ph/L)} \tag{5}$$

Flap type:

$$F(f,h) = \frac{H}{2e} = (\frac{4\sinh^2(2ph/L)}{4ph/L})(\frac{1- \cosh(2ph/L) + (2ph/L)\sinh(2ph/L)}{4ph/L + \sinh(4ph/L)}) \tag{6}$$

where H is the height of the produced wave in the channel; e is the amplitude of wave paddle at the mean water level; f stands for the wave frequency; L wavelength; h the depth of the water in front of the paddle in the channel. The Inverse Fourier Transform is applied to product of Eq. (3) or Eq. (4) and Eq (5) or Eq. (6) to obtain the wave signal in time domain. The Fig. 5 presents the process of the preparation of input signal to an irregular wave generator. The control systems, in general of open loop, need a relatively great time for the calibration of each experiment in order to generate a wave spectral pattern (target spectrum).

4 FeedForward Neural Network

For identification and control of systems a FNN (FeedForward Neural Network) with three layers is sufficient. A hidden layer is sufficient to identify any continuous function [11], [12], [14], [17]. The input neurons are determined by the number of frequency bands which the spectrum is divided. The tests were made with 128 and 64 inputs. The best results were obtained with 64 (training error and epochs). Another input neuron is added for the different water levels in the channel. The hidden layer uses a sigmoid function. The output layer uses a lineal function. The number of neurons of the output layer is determined by the number of frequency bands, which the generated wave spectrum will be divided (the output neurons were taken equal to the number of input neurons).

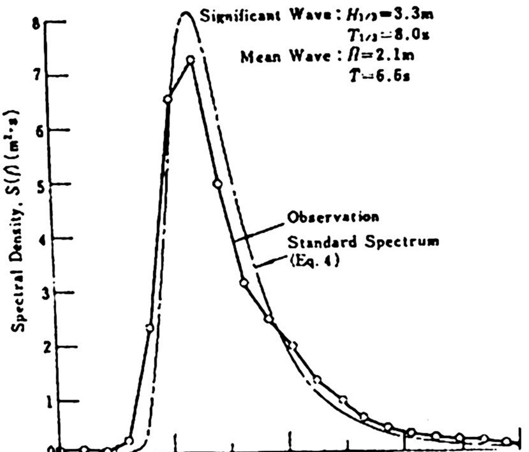

Fig. 4 Example of spectrum of sea waves

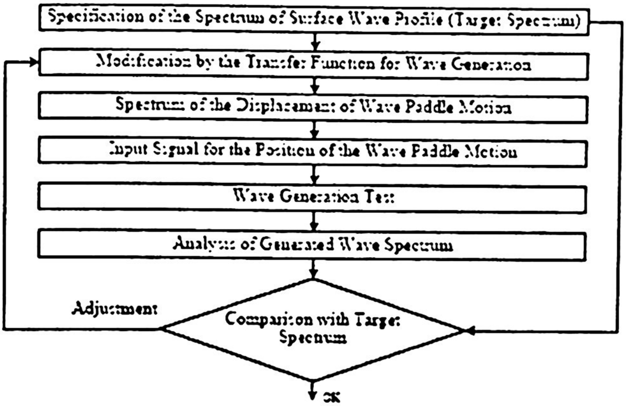

Fig. 5 Process of the preparation of input signal to an irregular wave generator

4.1 Training Patterns

The neural network topology is the following:

Input layer: 65 neurons. Output layer: 64 neurons. Hidden layer: 16 neurons.

Training Patterns:

P^{μ} : Input patterns [f(1), f(2),.........f(nf), h]

T_0^{μ} : Output patterns [$f_o(1)$, $f_o(2)$,.........$f_o(nf)$]

where f: power spectrum harmonics; h: channel level

Quality factor in the spectrum estimation:

Although the simulation of the sea disturbance is random (pseudorandom). The variability of the spectrum is given by:

$$\hat{S}(f) = S(f)\chi_2^2 \tag{7}$$

The variability of the spectrum is determined by a distribution of chi square with two degrees of freedom, that is the estimation by the periodogram method [2]. In order to reduce the variation, the temporary registry of the wave measurement is divided in a set of M windows.

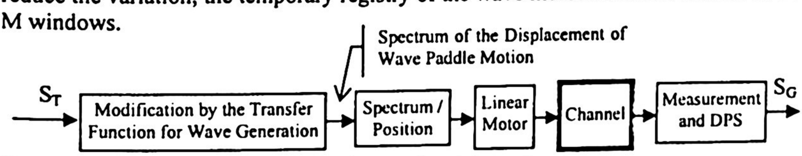

Fig. 6. Acquisition diagram for the neural network training patterns

The training patterns for neural network are obtained with the scheme of Figure 6.

4.1.1 Example of Patterns and Control Neural Performance

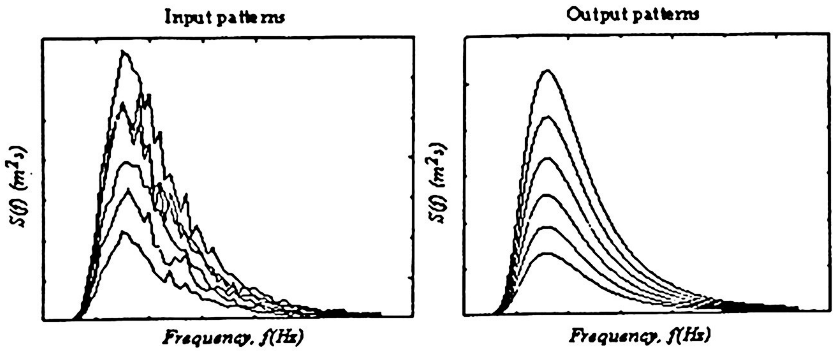

Fig. 7. Example of training patterns. Training performance is $6.97697e^{-10}$, Goal is $1e^{-10}$. Epochs: 25

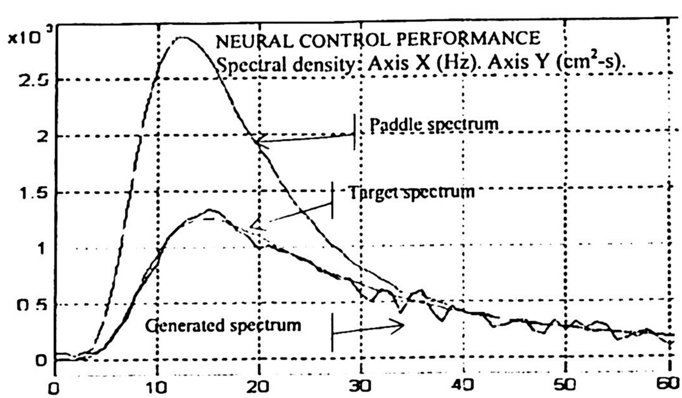

Fig. 8 Example 1 of neural control performance.

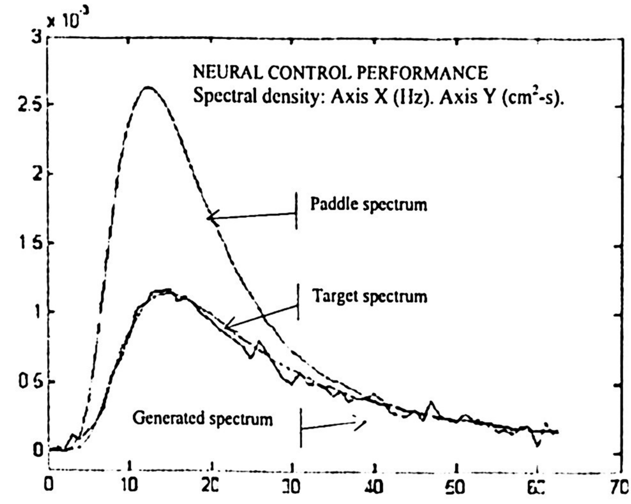

Fig. 9 Example 2 of neural control performance.

Conclusions and Future Work

The coastal and marine constructions are complex and highly expensive. The optimal design requires the physical modeling. The sea phenomena are reproduced in the research laboratories and the designs can be tested. This constructions are "pedraplenes", oil platforms, artificial beaches, protective installations of the coasts, conservation of the ecosystem, etc.

The presented work creates a novel method that uses linear motors and neural networks to generate irregular wave with high exactitude and fast calibration, obtaining itself satisfactory results. The control is made with a distributed architecture, because the linear motor has a system of independent control and it uses digital signal processing because the control variable is a power spectrum.

As future work, self-learning elements will be introduced. These elements will make possible to be creating spectral patterns during the operation of the system and to suggest a new training of the neural network, when the conditions of channel operation have great changes.

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