ADAPTIVE NEURAL NETWORK FILTERING DEVICE FOR ENHANCED DOWNHOLE OILFIELD MEASUREMENTS

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ABSTRACT

Slickline-deployed instruments are commonly used to perform measurement and service operations in oilwells. In order to accurately determine the downhole position of a suspended instrument, a device known as an electro-mechanical casing collar locator (EMCL) is sometimes used. The device is first lowered into a well, and then, slowly withdrawn. When a casing collar is encountered, the EMCL device causes changes in the line tension. These changes in line tension, which are measured at the surface, are correlated to collar locations, and hence, instrument depth. Like many other applications, noise from different sources during slickline jobs may add contaminating noise or cause destructive interference in the monitored of tension signals. In this paper, a method of using an adaptive neural network to filter the tension signal to remove unwanted noise is described. A theoretical discussion and the review of results of experimental testing are presented

1. INTRODUCTION

In a slickline depth measurement system, a tool is pulled at a constant velocity up the production tubing string. When the tool passes a joint in the tubing, a device is engaged to hold the tool momentarily at the position of the joint. This action causes a pulse in the tension of the wire, which is monitored at the surface. These pulses in tension can be used to determine the depth of each joint. In certain wells, the tension signal is corrupted by noise, and the tension pulses are not easily recognized.

Figure 1 represents the current slickline depth measurement system. A load cell is used to measure tension in the slickline cable. The slickline is wrapped around a measuring wheel that has an electrical counter to keep track of the motion of the wheel [1, 2, 3, 4, 6, 7, 8, 9]. The Advanced Measurement System (AMS) uses the signals from the load cell and the measuring wheel as well as ambient and downhole temperature-measurement adjustments to determine the length of slickline in the wellbore (as shown in **Figure 2**.) This is correlated with the tension pulses to determine the position of the tubing joints.

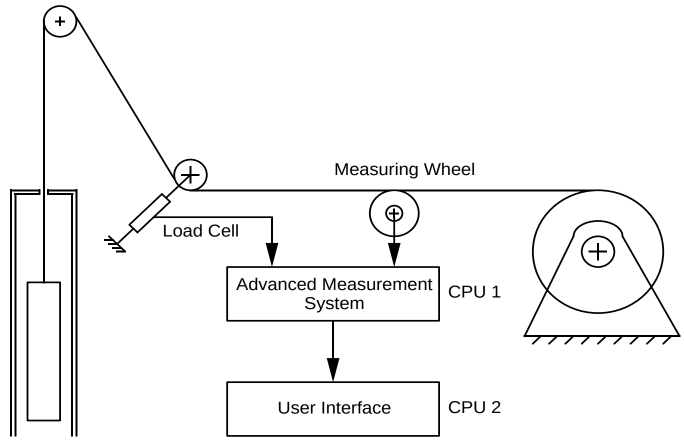

Figure 1. **Slickline Depth Measurement System (AMS).**

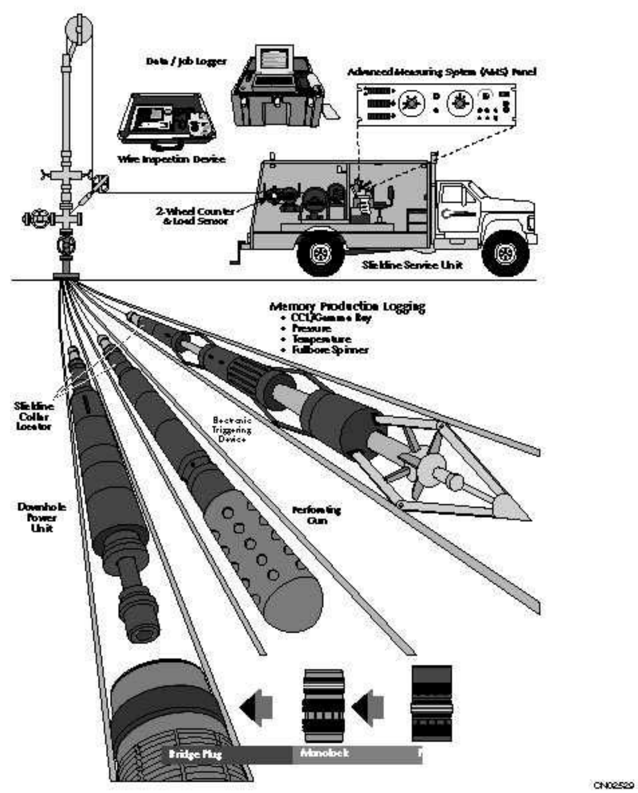

Figure 2. Field Implementation of Slickline with the Advanced Measurement System (AMS) [7].

The research discussed here focuses on the characterization of the load cell noise and on the development of procedures for reducing the levels of the noise. Eventually, we will provide a front-end slickline filter device, which can be used in conjunction with AMS, or implemented into AMS, as an additional building component to enhance slickline data.

This paper is organized as follows. In Section 2, we will discuss the proposed noise cancellation system and the adaptive filtering algorithm. In Section 3, we show the experiment results using filed data and simulation data. The summary of this work will be presented in section 4.

2. ADAPTIVE NOISE CANCELLATION SOFTWARE

2.1 Noise Cancellation System

Here, we assume that the contaminating noise is generated from a noise source that we can measure. A sample of the noise source is fed to a filter, whose elements are adjusted so as to minimize the error. The desired output of the filter is the contaminated signal. The filter will do its best to reproduce this contaminated signal, but it only has access to the original noise source. Thus, it can only eliminate the part of the contaminated signal that is correlated with the noise source, leaving the noise-free signal [10, 5].

For the slickline depth measurement system, the noise that resides on the tension signal could be caused by extraneous noise sources (such as surface machinery) or by improper tool installation and degraded downhole conditions, resulting in vibration that can be sensed by surface supporting frame where the tension sensor is located. We placed accelerometers and other sensors near potential noise sources and used these signals as inputs to a noise cancellation filter.

2.2 Adaptive Filter Equations

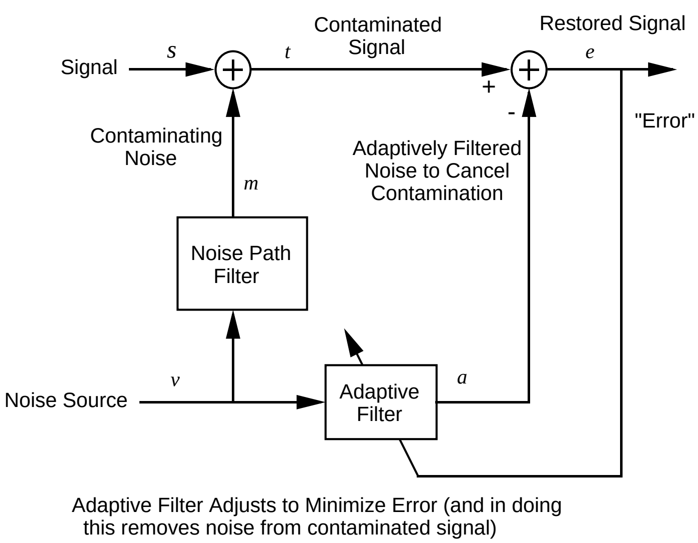

Figure 3. Noise Cancellation System

A layered neural network represents the filter, where the output is:

$$a^k(k) = NN(v(k), v(k-1), \ldots, v(k-n))$$

where *NN* represents a neural network transfer function like the one shown in Figure 4 with two layers (k = 2) and n delays.

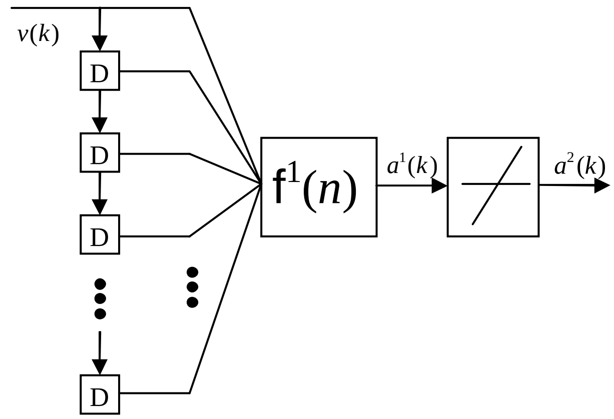

Figure 4. Adaptive Filter for Noise Cancellation.

The following relation updates the weights for the two-layer neural network example:

$$\mathbf{W}_{1,2}(k+1) = \mathbf{W}_{1,2}(k) + \alpha e(k)\mathbf{a}_1{}^T(k)$$

$$b_2(k+1) = b_2(k) + \alpha e(k)$$

$$\mathbf{W}_{1,1}(k+1) = \mathbf{W}_{1,1}(k) + \alpha e(k)\dot{\mathbf{f}}^1(n^1(k))\mathbf{v}^T(k)$$

$$b_1(k+1) = b_1(k) + \alpha e(k)\dot{\mathbf{f}}^1(n^1(k))$$

where $\mathbf{f}^1$ represents the nonlinear transfer function for the first layer, α is the learning rate (initial value set to 0.02), e(k) is the error between the desired load sensor value (target) and the neural network output for the time k. The default number of input delays is set to 10.

The operator could change the learning rate up to 0.2 and the number of input delays between 0 and 20. Each time one of the previous values is changed, a new neural network is created, and the training process is repeated again. After training, the user could select four possible views: the original signal coming from the load sensor, the filter input coming from the accelerometer, the filter output coming from the neural network, or the difference that is the error signal between the neural network and load sensor.

The last signal must be the load-sensor noise-free signal that is to be entered into the AMS unit.

3. EXPERIMENTAL RESULTS

3.1 Off-line tests

To test the adaptive noise cancellation, algorithm data were collected at the Carrollton testing well and at different wells in Wyoming during October and November 2001. In addition to the load sensor data and counter pulses, five different data strings were collected from accelerometers placed close to the load sensor and close to the cable drum. The initial data were collected at 5 kHz. For the demonstration included on this report, the data were down-sampled to 50 Hz.

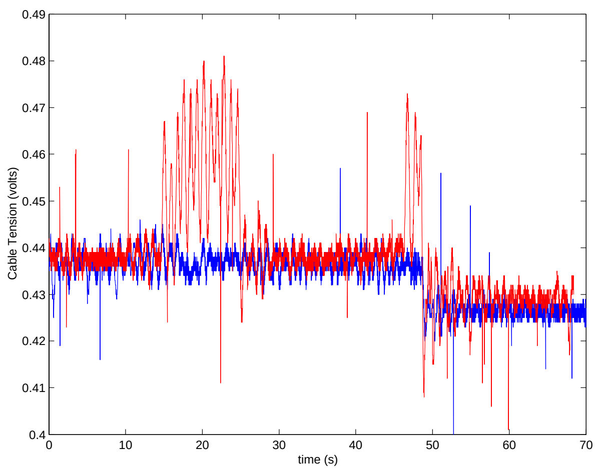

Figure 5. **Direct cable load data with collar locator off (blue) and on (red) at 90 ft./min.**

Figure 5 shows an example of data collected in Carrollton for the slickline ruining at 90 ft/min. The data in blue were collected with the collar locator in the "off" position, and the data in red were collected with the collar locator in the "on" position. We can notice the noise level present in both curves and the change in tension during collar detection. The tests performed here were for a filter with 10 tabs, a sampling rate of 50 Hz and gain $\alpha = 0.02$.

Figure 6 shows the plots for both experiments after the adaptive filter is applied. This figure shows that the two collar-location conditions are noticeable as well as the change in tension due to the change in the casing dimensions.

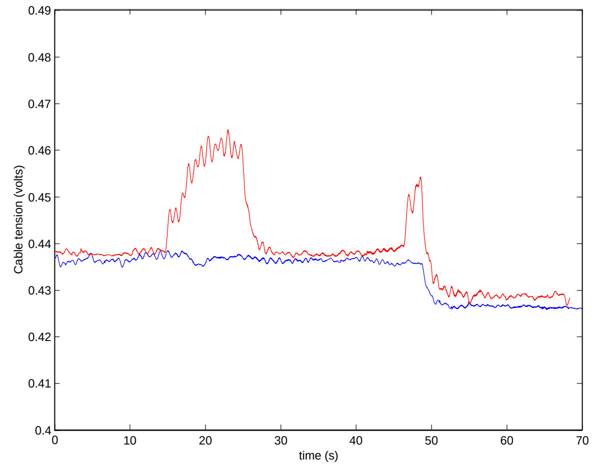

Figure 6. Filtered cable load data with collar locator off (blue) and on (red) at 90 ft/min.

Figure 7 shows the neural network output where we found a correlation between the noise present at the system that was removed for each of the data streams collected from the load sensor.

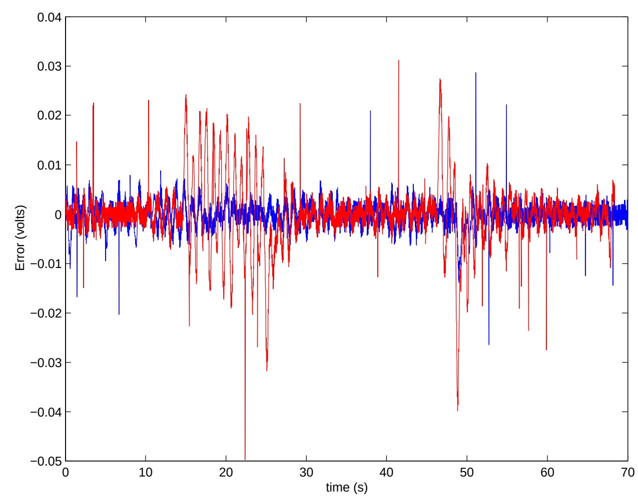

Figure 7. Neural Network output with collar locator off (blue) and on (red) at 90 ft./min.

On-line tests.

Figure 8 shows the original collar locator and filtered signals when a noise of 0.03 volts peak-to-peak is affecting the measurements. For the online experiments, a 40 tabs filter was used at a sampling rate of 60 Hz and gain α=0.1. The graphic shows that the clear collar locator signal is recovered. **Figure 9** shows similar graphs when the noise is increased to 0.1 volts peak-to-peak. We could see that the recovered signal is still noisy, but the collar signals pulses could be easily identified.

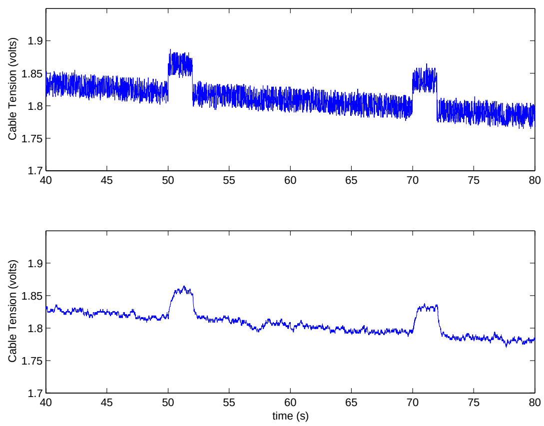

Figure 8. Original collar locator signal (top) and Neural Network output (bottom) at 60 ft/min and noise 0.03 v.

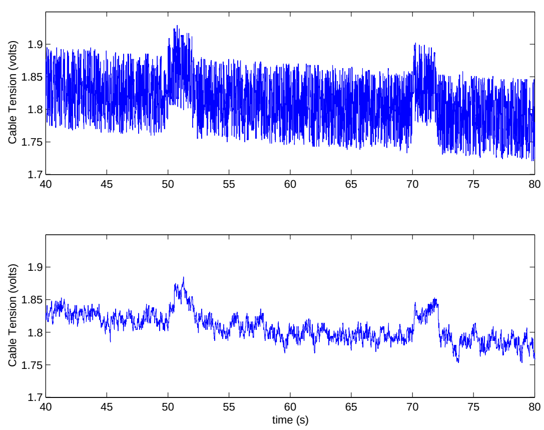

Figure 9. **Original collar locator signal (top) and Neural Network output (bottom) at 60 ft./min and noise 0.1 v.**

SUMMARY

In this paper, we have demonstrated a noise cancellation algorithm for a downhole slickline tool used in oilfield. The algorithm correlates a reference noise input at the job site with the primary slickline data input. The noise can be "subtracted" from the received signal, allowing us to guarantee greater immunity to environmental interference. A simple neural network adaptive filter was used in this application for the sake of fast on-line training and a synchronization requirement with other signals.

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