

# Fundamentals of Signal Processing and Data Analysis

## Homework 2

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### 1 A Digital Filter Given by the Difference Equation

We are given a digital filter described by:

$$y[n] = x[n] + 0.1 y[n-1], \quad \text{with } y[-1] = 0$$

We are to find the impulse response and the step response of this system.

#### 1.1 Recurrence Expansion

$$y[n] = x[n] + 0.1 y[n-1] \tag{1}$$

$$y[n-1] = x[n-1] + 0.1 y[n-2] \tag{2}$$

Subtracting (2) from (1):

$$y[n] - y[n-1] = x[n] - x[n-1] + 0.1 (y[n-1] - y[n-2]) \tag{3}$$

#### 1.2 The Impulse Response

Define the unit impulse:

$$\delta[n] = \begin{cases} 1, & n = 0 \\ 0, & n \neq 0 \end{cases}$$

Substitute  $x[n] = \delta[n]$  into the difference equation:

$$y[n] = \delta[n] + 0.1 y[n-1]$$

When  $n = 0$ :

$$y[0] = 1$$

When  $n > 0$ ,  $\delta[n] = 0$ , so:

$$y[n] = 0.1 y[n-1] = 0.1^n$$

For  $n < 0$ , from the initial condition  $y[-1] = 0$ , and backward recursion, we find that:

$$y[n] = 0 \quad \text{for all } n < 0$$

Thus, the impulse response is:

$$h[n] = y[n] = \begin{cases} 0.1^n, & n \geq 0 \\ 0, & n < 0 \end{cases}$$

### 1.3 The Step Response

#### 1st Method (Recursive)

Define the step function:

$$u[n] = \begin{cases} 1, & n \geq 0 \\ 0, & n < 0 \end{cases}$$

Using the difference equation with  $x[n] = u[n]$ :

$$\begin{aligned} y[0] &= u[0] + 0.1 y[-1] = 1 \\ y[1] &= u[1] + 0.1 y[0] = 1 + 0.1 = 1.1 \\ y[1] - y[0] &= 0.1 \end{aligned}$$

For  $n > 1$ , since  $x[n] = x[n-1] = 1$ , equation (3) becomes:

$$y[n] - y[n-1] = 0.1 (y[n-1] - y[n-2])$$

This is a geometric progression:

$$y[n] - y[n-1] = 0.1^n, \quad n \geq 1$$

So the total change from  $y[0]$  is:

$$y[n] - y[0] = \sum_{k=1}^n 0.1^k = \frac{1 - 0.1^n}{9}$$

Thus:

$$y[n] = y[0] + \frac{1 - 0.1^n}{9} = 1 + \frac{1 - 0.1^n}{9} = \frac{10 - 0.1^n}{9}$$

**Therefore, the step response is:**

$$y[n] = \begin{cases} \frac{10 - 0.1^n}{9}, & n \geq 0 \\ 0, & n < 0 \end{cases}$$

## 2nd Method (Convolution)

Use the impulse response  $h[n] = 0.1^n$  for  $n \geq 0$ , and zero otherwise.

By convolution:

$$\begin{aligned} y[n] &= u[n] * h[n] = \sum_{i=-\infty}^{\infty} u[i] h[n-i] \\ &= \sum_{i=0}^n h[n-i] = \sum_{k=0}^n 0.1^k \\ &= \frac{1 - 0.1^{n+1}}{1 - 0.1} = \frac{10 - 0.1^{n+1}}{9} \end{aligned}$$

Note: This matches the previous result with a one-index shift.

**Final result:**

$$y[n] = \begin{cases} \frac{10 - 0.1^{n+1}}{9}, & n \geq 0 \\ 0, & n < 0 \end{cases}$$

## 2 Proof That Two Cascaded LTI Systems Yield the Same Output

We aim to prove that cascading two LTI systems with impulse responses  $h_1[n]$  and  $h_2[n]$  produces the same output regardless of their order:

$$(x[n] * h_1[n]) * h_2[n] = (x[n] * h_2[n]) * h_1[n]$$

### Step 1: Use Commutativity of Convolution

$$(x[n] * h_1[n]) * h_2[n] = (h_1[n] * x[n]) * h_2[n]$$

### Step 2: Prove Associativity of Convolution

We now show that:

$$(h_1[n] * x[n]) * h_2[n] = h_1[n] * (x[n] * h_2[n])$$

Compute the left-hand side:

$$\begin{aligned} (h_1[n] * x[n]) * h_2[n] &= \left( \sum_{\tau=-\infty}^{\infty} h_1[\tau] x[n-\tau] \right) * h_2[n] \\ &= \sum_{t=-\infty}^{\infty} \left( \sum_{\tau=-\infty}^{\infty} h_1[\tau] x[t-\tau] \right) h_2[n-t] \\ &= \sum_{\tau=-\infty}^{\infty} h_1[\tau] \sum_{t=-\infty}^{\infty} x[t-\tau] h_2[n-t] \end{aligned}$$

Make a change of variable: let  $\eta = t - \tau$ , so  $t = \eta + \tau$ :

$$\begin{aligned}
&= \sum_{\tau=-\infty}^{\infty} h_1[\tau] \sum_{\eta=-\infty}^{\infty} x[\eta] h_2[n - (\eta + \tau)] \\
&= \sum_{\tau=-\infty}^{\infty} h_1[\tau] \left( \sum_{\eta=-\infty}^{\infty} x[\eta] h_2[n - \tau - \eta] \right) \\
&= \sum_{\tau=-\infty}^{\infty} h_1[\tau] (x[n - \tau] * h_2[n - \tau]) \\
&= h_1[n] * (x[n] * h_2[n])
\end{aligned}$$

### Step 3: Use Commutativity Again

$$h_1[n] * (x[n] * h_2[n]) = (x[n] * h_2[n]) * h_1[n]$$

### Conclusion:

Combining all steps:

$$(x[n] * h_1[n]) * h_2[n] = (x[n] * h_2[n]) * h_1[n]$$

Therefore, the outputs of the two LTI system configurations are the same, confirming that cascading LTI systems is order-independent due to the commutativity and associativity of convolution.