

# Report 3

## Modeling and Identification

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### 1 Regression Estimation

The problem of regression estimation is shown on Fig 1. We have the input signal  $U_k$ , the output signal of unknown regression function  $Y_k$ , and the noise  $Z_k$  which is the part of the output. Our goal is to estimate function  $\mu()$  by measuring the input and the output values. To make it consistent we need to add some assumptions:

- $\mu() \rightarrow$  is continuous function,
- $EZ_k = 0$ ,
- $var Z_k < \infty$ ,
- $U_k$  and  $Z_k$  are independent.

To accomplish this goal we use two methods: Kernel Regression Estimator and Orthogonal Expansion Method. Description of each method is presented below.

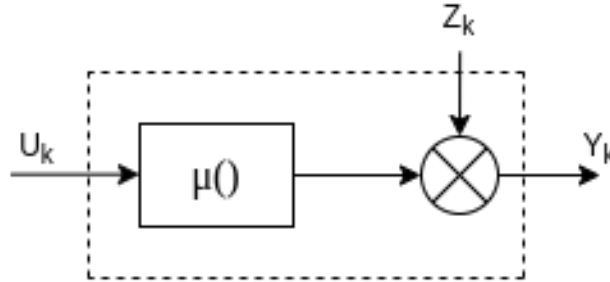


Figure 1: Diagram of Regression Estimation

#### 1.1 Kernel Regression Estimator

Formula for estimating  $\mu()$  function by Kernel Regression Estimator looks like this:

$$\hat{\mu}(u) = \frac{\sum_{k=1}^N y_k K\left(\frac{u_k - u}{h}\right)}{\sum_{k=1}^N K\left(\frac{u_k - u}{h}\right)}$$

where:

$$K(u) = \begin{cases} 1 & : |u| < h \\ 0 & : elsewhere \end{cases}$$

$h$  - size of kernel window.

## 1.2 Orthogonal Expansion Method

Formula for estimating  $\mu()$  function by Orthogonal Expansion Method looks like this:

$$\hat{\mu}(u) = \frac{\sum_{i=1}^S \hat{b}_i \varphi_i(u)}{\sum_{i=1}^S \hat{a}_i \varphi_i(u)}$$

where:

$$\begin{aligned} \hat{a}_i &= \frac{1}{N} \sum_{k=1}^N \varphi_i(u_k) \\ \hat{b}_i &= \frac{1}{N} \sum_{k=1}^N y_k \varphi_i(u_k) \\ \varphi_i(x, i) &= \begin{cases} \frac{1}{\sqrt{2}} & \text{if } i = 1 \\ \sin(\frac{i}{2}\pi x) & \text{if } i \text{ is even} \\ \cos(\frac{i-1}{2}\pi x) & \text{if } i \text{ is odd} \end{cases} \end{aligned}$$

## 2 Experiments

The function that was chosen as  $\mu$  is:

$$\mu(u) = \lfloor u * 5 \rfloor$$

Then the 100 random arguments were chosen from interval  $[-1,1]$ , values for them was calculated from  $\mu$  function and the noise  $(2*\text{rand}()-1)$  was added. Next step was to estimate function  $\mu$  using samples with noise.

### 2.1 Kernel Regression Estimator

Plot of the estimated function  $\mu$  by Kernel Regression Estimator with  $h=0.1$  is shown on Fig 2. Relationship between value of  $h$  and corresponding MSE is shown on Fig 3.

### 2.2 Orthogonal Expansion Method

Plot of the estimated function  $\mu$  by Orthogonal Expansion Method with  $S=5$  is shown on Fig 4. Relationship between value of  $h$  and corresponding MSE is shown on Fig 5.

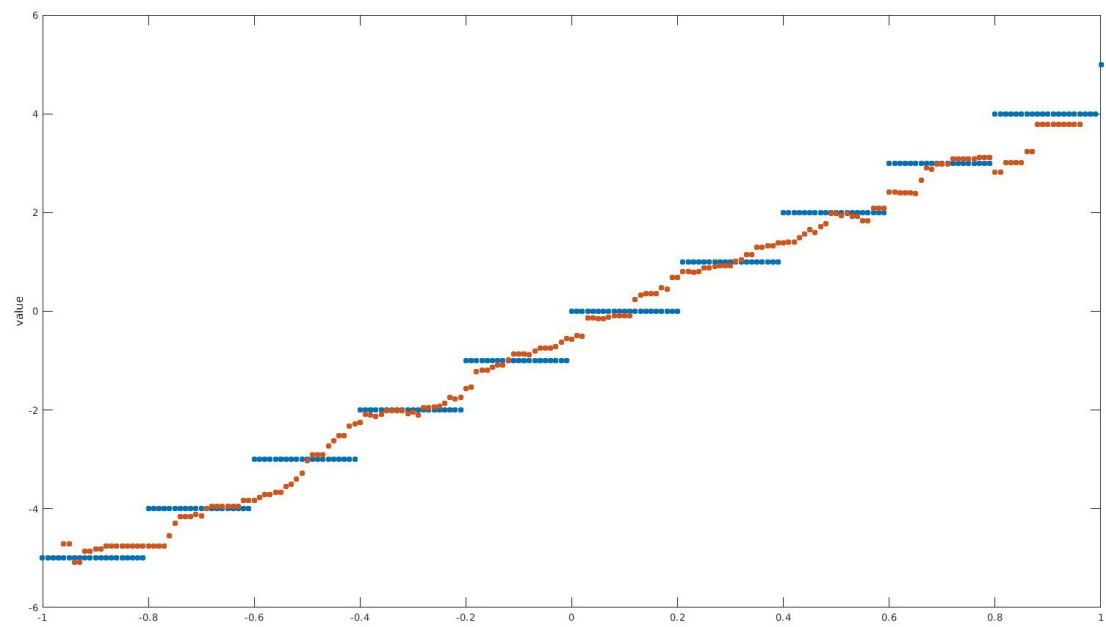


Figure 2: Estimated  $\mu$  function for  $h=0.1$ .

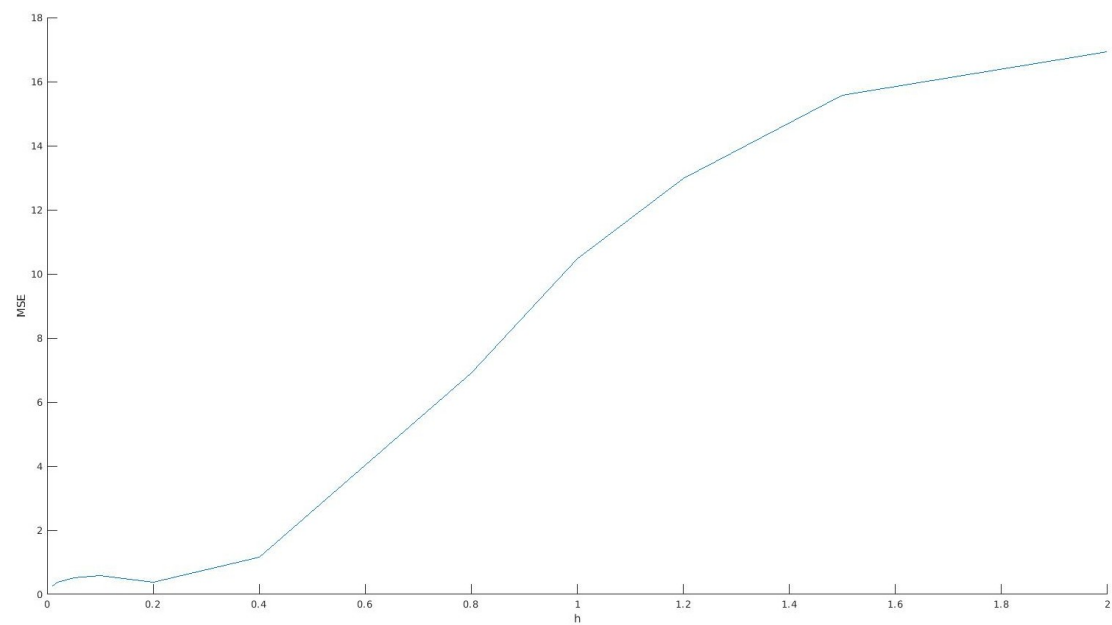


Figure 3: Relationship between MSE and  $h$  value for Kernel Regression Estimator.

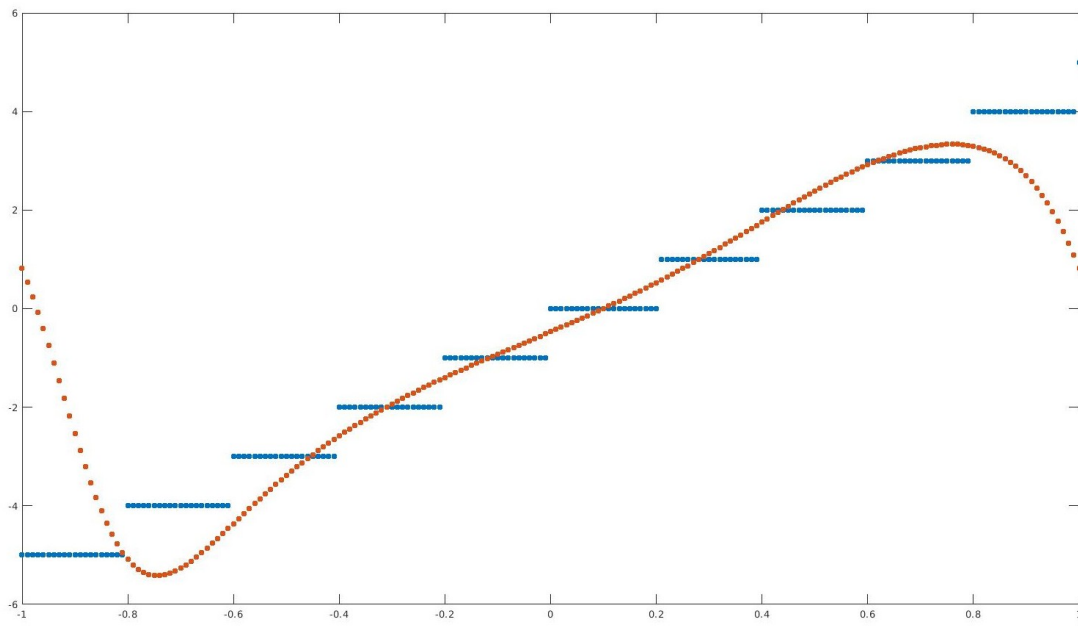


Figure 4: Estimated  $\mu$  function for  $S=5$ .

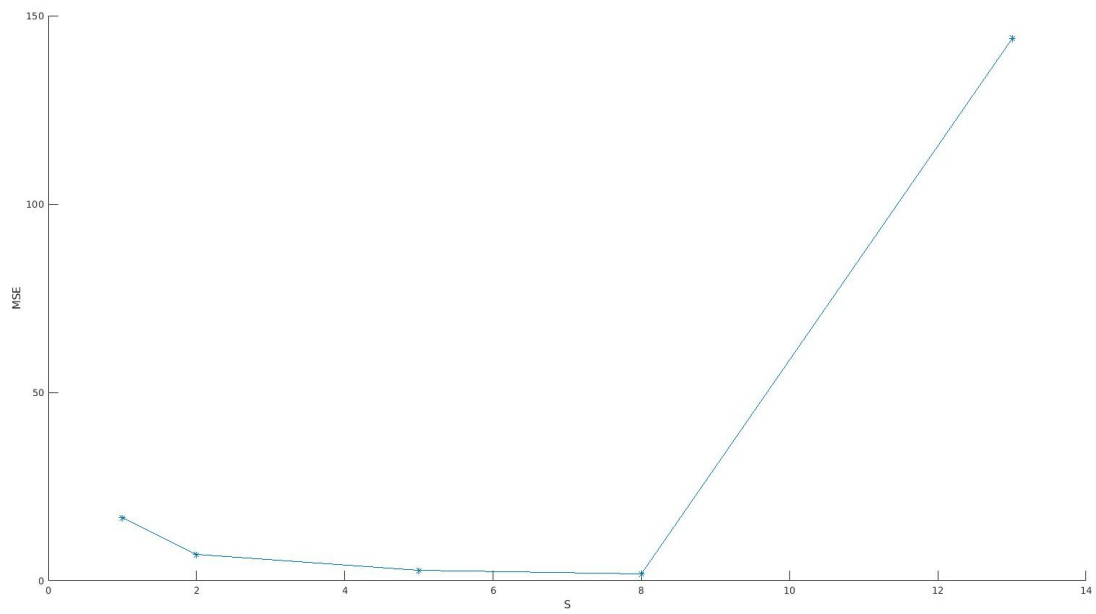


Figure 5: Relationship between MSE and  $h$  value for Orthogonal Expansion Method.