## The max-MSE's of minimax estimators of variance in nonparametric regression

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## 1. Introduction and notations

Consider the nonparametric regression model

$$Y_i = g(t_i) + \varepsilon_i$$
,  $1 \le i \le n$ 

where observations are taken at design points  $t_i$  for  $1 \le i \le n$ , and the errors  $\varepsilon_i$  are independent and identically distributed as normal distribution with mean zero and variance  $\sigma^2$ . The response function g is assumed to belong to the space  $W = \{g : g \text{ and } g' \text{ are absolutely continuous, and } \int_0^1 |g''(t)|^2 dt < \infty \}$ .

We deal with minimax estimators of  $\sigma^2$  defined in Buckley, Eagleson and Silverman [1]. They are based on a restricted class of the response functions  $W_C = \{g \in W : \int_0^1 |g''(t)|^2 dt \le C\}$ . Define the max-MSE criterion as

$$M(\hat{\sigma}^2; \sigma^2, C) = \max_{g \in W_C} \frac{1}{\sigma^4} E(\hat{\sigma}^2 - \sigma^2)^2$$

for any given estimator  $\hat{\sigma}^2$  of  $\sigma^2$ . To simplify the minimax problem, we shall use a natural coordinate system. Demmler and Reinsch [2] showed that there is a basis for the natural cubic splines,  $\phi_1(\cdot)$ , ...,  $\phi_n(\cdot)$ , determined essentially uniquely by

$$\sum_{i=1}^n \phi_j(t_i)\phi_k(t_i) = \delta_{jk}, \qquad \int_0^1 \phi_j''(t)\phi_k''(t)dt = \delta_{jk}\omega_k$$

with  $0 = \omega_1 = \omega_2 < \cdots < \omega_n$ . Here  $\delta_{jk} = 1$  if j = k and 0 otherwise. Let  $\tilde{y} = (Y_1, \ldots, Y_n)^T$  and  $\tilde{g} = (g(t_1), \ldots, g(t_n))^T$  be the vectors expressed with respect to a natural basis of  $\mathbb{R}^n$ ,  $\{(\phi_j(t_i))\}$ . Our attention is restricted to a class of estimators of  $\sigma^2$  whose form is  $\hat{\sigma}^2(D) = \tilde{y}^T D \tilde{y} / \text{tr } D$ ,  $D \in \Delta$ . Here  $\Delta$  is the class of  $n \times n$  symmetric non-negative definite matrices D for which  $\hat{\sigma}^2(D)$  is unbiased when g is a straight line. Buckley, Eagleson and Silverman [1] proposed minimax estimators defined as the estimator which minimizes  $M(\hat{\sigma}^2(D); \sigma^2, C)$  over  $D \in \Delta$ . Their minimax estimators depend on  $\sigma^2$  and C through  $C/\sigma^2$ . The explicit expressions of them were obtained in Fujioka [3] as follows. Putting  $\omega_i^+(r) = \omega_i (1 + 4\omega_i/r)^{-1/2}$  for  $3 \le i \le n$ , we set for  $3 \le k \le n - 1$