Supplementary material for

Local and Global Structure-Guided No-Reference Point Cloud Quality Assessment

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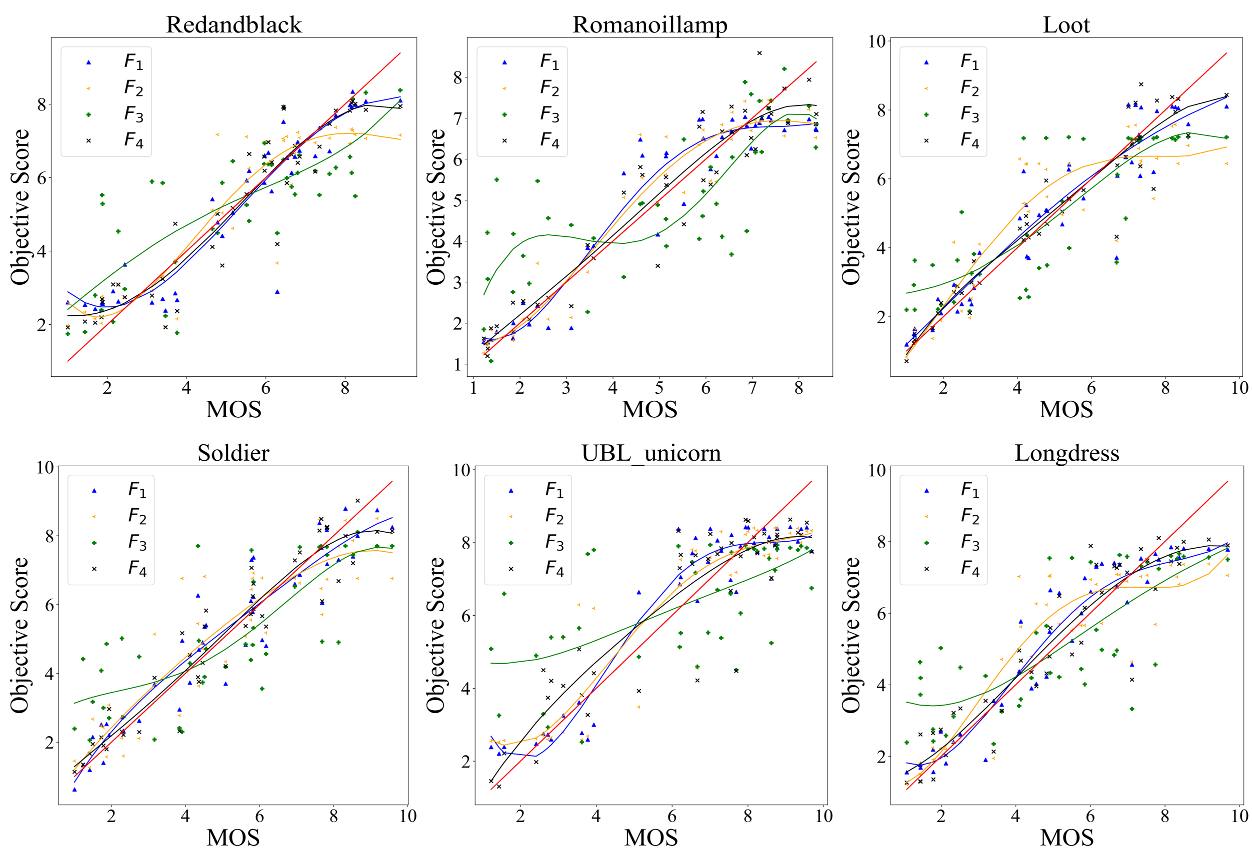
In this supplementary material, to express the influence of different feature combinations $F_1 \sim F_4$ (i.e., F_1 is geometry + color, F_2 is geometry + curvature, F_3 is curvature + color, F_4 is geometry + color + curvature) on quality prediction performance more intuitively, we have provided the scatter plots shown in Fig. 9 for all four feature combinations. The performance with feature combination F_1 is better than that with F_4 in terms of "Statue". However, for most of the samples, F_4, represented by the black curve, is closer to the red perfect-prediction line than the other curves are. This finding demonstrates that F_4 is the most effective and characterizes the PC quality more comprehensively.



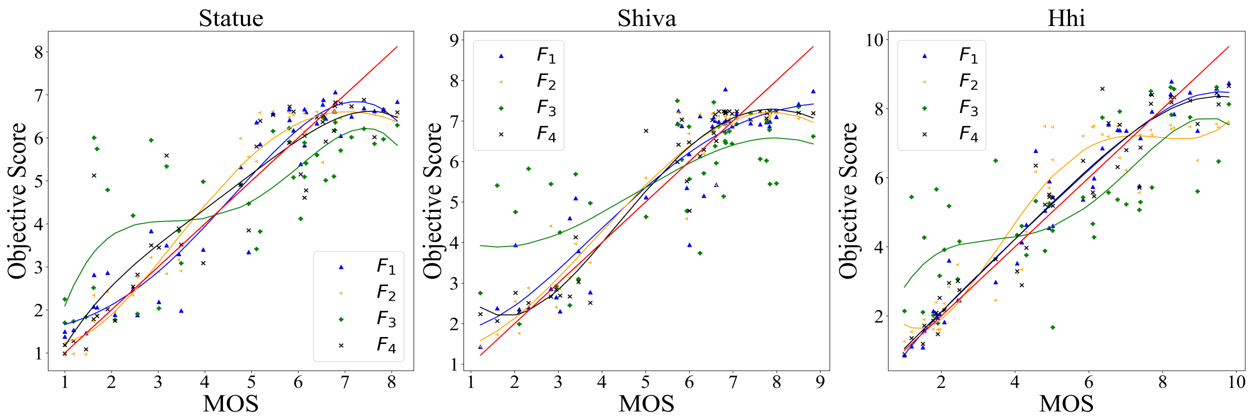


Fig. 9: Objective scores for different input feature sets in the SJTU-PCQA database, where the red line indicates that the objective scores are closer to the MOS.

Additionally, to verify whether the selection of θ demonstrates generalizability across other datasets, we conducted experiments on the CPCD2.0 dataset. As shown in the Table XI, the performance of the high-pass2 method with θ set to $N/1000$ consistently outperforms that with θ set to $N/5000$ and $N/10000$. This suggests that the selection of θ as $N/1000$ is not only optimal for the SJTU-PCQA dataset but also demonstrates strong performance on the CPCD2.0 dataset.

TABLE XI: EXPERIMENTAL RESULTS USING THE CPCD2.0 DATASET FOR DIFFERENT SAMPLING RATES UNDER HIGH-PASS2 METHOD

$\boldsymbol{\theta}$	$N/1000$	$N/5000$	$N/10000$
SROCC	**0.848**	0.801	0.757
PLCC	**0.832**	0.752	0.749