INTERACTIVE DEMONSTRATIONS OF THE LOCALLY ADAPTIVE FUSION FOR COMBINING OBJECTIVE QUALITY MEASURES

Adriaan Barri[1,2], *Ann Dooms*[1,2], *Peter Schelkens*[1,2]

[1]Vrije Universiteit Brussel (VUB), Dept. of Electronics and Informatics (ETRO), Pleinlaan 2, B-1050 Brussels, Belgium.
[2]iMinds, Dept. of Future Media and Imaging (FMI), Gaston Crommenlaan 8 (box 102), B-9050 Ghent, Belgium.
{abarri,adooms,pschelke}@etro.vub.ac.be.

ABSTRACT

To automate quality monitoring of multimedia applications, objective quality measures for images and video content need to be designed. Objective quality measures that model the Human Visual System (HVS) have a disappointing performance, because the HVS is not sufficiently understood. Integrating machine learning (ML) techniques may increase the performance. Unfortunately, traditional ML is difficult to interpret. To this end, we developed the Locally Adaptive Fusion (LAF), for more flexible and reliable quality predictions. This manuscript proposes six interactive programs and a website that demonstrate the effectiveness of LAF, which complement the technical focus of the corresponding journal paper.

***Index Terms*—** Objective quality assessment, machine learning, locally adaptive fusion.

1. INTRODUCTION AND MOTIVATIONS

Objective quality measures to automatically predict the visual quality can improve the performance of end-to-end quality monitoring in a broad range of applications. Objective quality measures can be constructed in two ways: by modeling the Human Visual System (HVS) or by integrating Machine Learning (ML).

Quality measures based on HVS modeling rely on explicit, mathematical models of important perceptual mechanisms. As an advantage, modeling the HVS ensures the quality predictions are completely transparent. Unfortunately, the HVS is very complex and currently not completely understood. As a result, HVS-based quality measures are computationally very expensive, while the increase in prediction accuracy over the PSNR is limited. These important drawbacks triggered the design of objective quality measures based on Machine Learning (ML) [1, 2]. These ML-based objective quality measures try to mimic the HVS mechanisms and do not require explicit mathematical models.

Although many ML-based objective quality measures have been disclosed previously, there is quite some room for improvement. While ML systems with a linear response cannot handle the complex behavior of the HVS, traditional ML systems with a nonlinear response are often difficult to analyze and interpret, which increases the risk of vulnerabilities in the construction. Examples of such vulnerabilities are consistency violations, unstable predictions in the high quality range, and severe false orderings, as explained in Figs. 10-12 of the corresponding paper [2] .

Our *Locally Adaptive Fusion* (LAF) system, proposed in [2], addresses the issues of ML inherent to quality assessment by imposing strict regulations on the ML behavior. These regulations significantly increase the reliability of the quality predictions. The LAF system improves upon traditional ML in many different ways. By construction, the LAF system is:

1. **Adaptive.** The weights used to combine the input quality measures are adapted to the characteristics of the received signal.
2. **Interpretable.** The weights of LAF are directly related to the input quality measures. Interpretable systems are less prone to vulnerabilities of the quality predictions.
3. **Optimized on the entire quality range.** By cleverly combining multiple locally optimized fusion units, the LAF system can achieve a high quality prediction accuracy on the entire quality range.
4. **Reproducible.** Unlike neural networks, the training of the LAF system does not require a random initialization. Hence, re-training the LAF system on the same data always produces the same weights.
5. **Always consistent with its input.** Say one image gets a higher quality score than another by all input quality measures. Then LAF will always assign a higher quality score to the first image as well. Traditional machine learning often violates the consistency rule: they tend to ignore the information provided by the input quality measures to better fit the training data.
6. **Computationally scalable.** The LAF system can be easily configured to find the optimal trade-off between computational complexity and prediction accuracy.

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2. SCIENTIFIC AND TECHNICAL DESCRIPTION

The *Locally Adaptive Fusion* (LAF) is a novel system specifically designed for flexible and reliable combinations of objective quality measures. The complete technical description of the LAF system can be found in [2]. In short, LAF predicts the quality of a newly received signal x in two steps.

In the first step, the received signal x is subjected to multiple *fusion units* U_i, $i = 1, 2, \ldots, n$. These units are weighted sums of a plurality of objective quality measures M_j, $j = 1, 2, \ldots, m$ using a first set of *fixed weights* $w_{i,j}$. This yields fusion unit values $U_i(x)$. Every fusion unit U_i is associated with a fixed *target value* r_i. The distance between each measurement fusion value $U_i(x)$ and the corresponding target value r_i gives an indication of the probability of the target value being the true unknown perceptual quality.

In the second step, the perceptual quality of the signal x is predicted by combining the fusion unit values with a second set of *adaptive weights* $W_i(x)$. The weight values change in function of the signal, depending on their distances to r_i.

3. IMPLEMENTATION AND USE

The corresponding paper focuses on the technical aspects of the LAF system (mathematical derivations, proofs, and statistical validations). For a better understanding of the theoretical framework, practitioners will benefit from interactive demonstrations that further explain the advantages of LAF. Therefore, we propose to present six interactive programs that demonstrate the six advantages of LAF listed in Section 1. To facilitate the illustration, we designed an attractive website on the LAF system, which was recently uploaded to `www.locally-adaptive-fusion.com`.

1. **Clarification of the weighting mechanism** that ensures LAF is adapted to the signal (Fig. 1).
2. **Interpretation of the adaptive weights** by relating them to the input measures (Fig. 2).
3. **Calculation of the separation ratio** to optimize LAF on the entire quality range (Fig. 3).
4. **Optimization of the fixed weights** where the convexity ensures reproducibility (Fig. 4).
5. **Visualization of the falsely ordered pairs** caused by inconsistencies of traditional ML (Fig. 5).
6. **Generation of the selected fusion units** which determine the amount of computations (Fig. 6).

4. CONCLUSION

The *Locally Adaptive Fusion* (LAF) system provides innovative solutions for the issues of Machine Learning (ML) inherent to quality assessment. As a result, the LAF system is more suitable than traditional ML for real-life applications. A website and six interactive demonstrations were created to convince the practitioners of all the benefits.

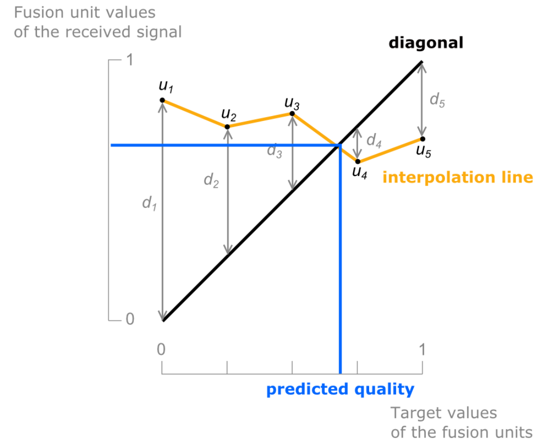

Fig. 1. The first demo clarifies the adaptive weighting mechanism of LAF. The user chooses an image in the stress test database. The program calculates the corresponding fusion unit values u_1 and u_5 and plots the interpolation line. The shorter the distance d_i to the diagonal, the more reliable the quality indication u_i. The optimal quality prediction is the intersection of the interpolation line and the diagonal [2].

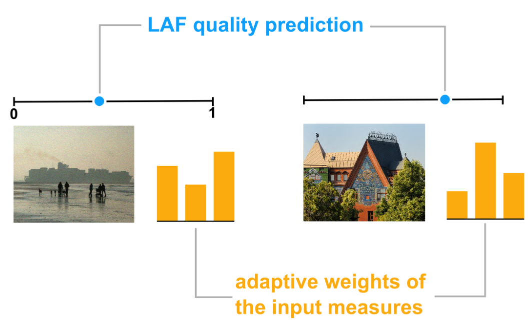

Fig. 2. The second demo shows how LAF can be interpreted. The user selects any image in the stress test database. The program then calculates the adaptive weights assigned to the quality measures and outputs the LAF quality prediction. The direct relation between the adaptive weights and the input quality measures makes LAF interpretable.

5. REFERENCES

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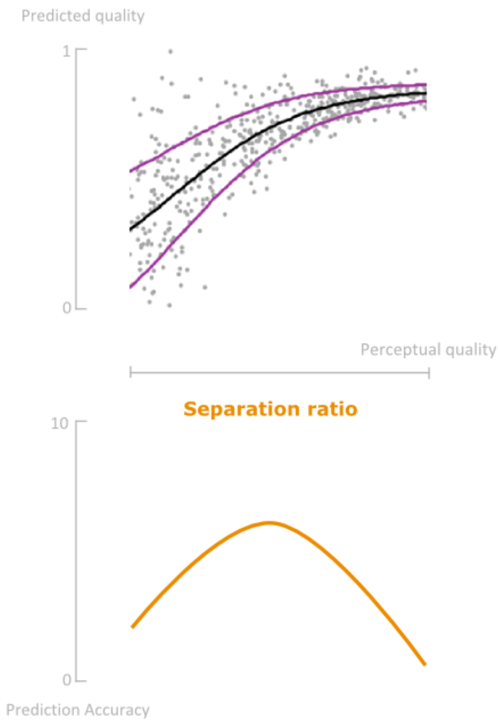

Fig. 3. The third demo explains the calculation of the separation ratio. The user specifies a conditional mean function and a confidence band. The program simulates data that corresponds to a hypothetical measure with the user-specified parameters. For this hypothetical quality measure, the separation ratio is visualized, which measures the local prediction accuracy in function of the perceptual quality.

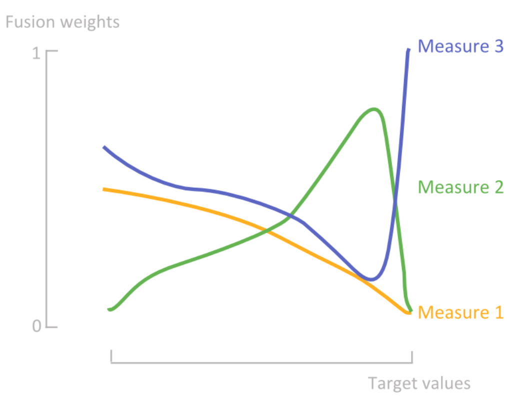

Fig. 4. The fourth demo focuses on the optimization of the fixed weights that build up the fusion units. The user inputs the target value of a fusion unit (any value between 0 and 1). The program outputs the corresponding convex quadratic optimization problem and shows how this optimization problem is solved. The solution gives the weights of the user-specified fusion unit.

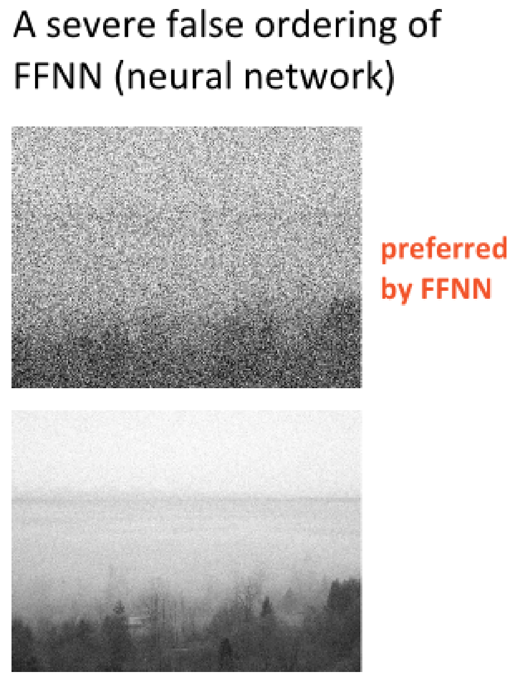

Fig. 5. The fifth demo allows the user to query the falsely ordered image pairs in the stress test database (119 for PCR, 2383 for GRNN, 342 for PCR, and 6 for LAF [2]). The user can select one of these false orderings and the program returns the corresponding image pairs.

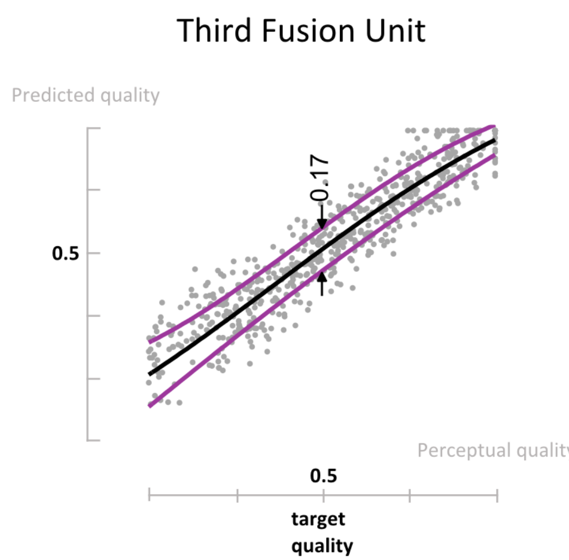

Fig. 6. The sixth demo focuses on the fusion units. The more fusion units are selected, the higher the prediction accuracy of LAF at the cost of a higher computational complexity. The user specifies a target value (any value between 0 and 1) and the program outputs the corresponding fusion unit.