Face image quality assessment

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Prior works in face image quality assessment have offered many techniques to effectively measure different quality factors. A first common approach in the literature is to analyse individual properties responsible for degrading recognition performance. Authors in presented a method for illumination normalization, based on retina modelling, capable of improving FR under challenging illumination conditions. Similarly, Gao et al. proposed to measure facial asymmetry due to sided lighting and non-frontal pose to assess quality deteriorations. Another example is the super-resolution algorithm introduced in, designed to pre-process improve low-resolution video frames. However, all these publications only take into account a single or few quality factors, which does not authentically represent the variability of a real-case scenario.

Other papers propose to measure face image quality as the degree of similarity against a reference ideal image (usually uniformly illuminated, with a neutral expression and frontal pose). For instance, authors of used the well-known universal image quality index to measure luminance distortion in comparison to a known reference image. This allowed to adaptively select fusion parameters of a face recognition system. Wong et al. developed a patch-based FIQA algorithm for video face recognition which measures the similarity between a face image and a probabilistic model, representing an ideal face. Moreover, Best-Rowden et al. applied Structural SIMilarity (SSIM) index for quality-based fusion and video frame selection. Unfortunately, reference-based methods are limited by the assumptions on a standard face. Selecting empirical reference images may lead to a bad generalization when evaluating other databases, images affected by many quality issues or real scenarios. In addition, these approaches do not fully take advantage of the robustness of recent FR algorithms, which can deal with face occlusions, bad illumination and pose variations.

Lately, the literature has focused its attention on metrics capable of considering multiple quality factors. Due to the proliferation of many unconstrained databases, the interest on learning-based FIQA models has considerably increased. The main advantage of these approaches is that they allow adapting the quality to a specific FR algorithm. The method in presented a Bayesian model to describe the relationship between image quality and face recognition performance. However, it required a large number of training samples densely spread in the quality space. Similarly, Zohra et al. published a linear regression model to adjust the weights of several quality factors by their impact on FR. Authors of proposed a method based on learning to rank4 a face image between three different quality-type databases (controlled scenario, uncontrolled scenario, and non-face). They trained a Convolutional Neural Network (CNN) extracting up to five different image features and eventually mapping the results into a quality score between 0−100.

Moreover, Vignesh et al. presented an algorithm based on modelling the recognition capability of a given FR system using a CNN. Basically, authors used the prediction of similarity score as a FIQA metric under the assumption that the quality of an enrolment image is as good as the quality of a probe image. Going further, L. Best-Rowden and A. K. Jain compared the use of similarity scores and human assessments for learning face image quality. The proposed method performed equivalently to Chen et al. in the IJB-A database. Lastly, authors in also introduced a learning-based approach where two factors for face image quality were considered: visual quality and mismatch between training and test images. They trained a FIQA model by employing an AdaBoost algorithm to distinguish useful faces from useless ones.