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# GLOBAL CONTRAST ENHANCEMENT USING SMI & PR ALGORITHMS

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***Abstract*— Image enhancement is one of the challenging issues in low level image processing. In general, it is difficult to design a visual artifact free contrast enhancement method. Considering this, we propose a global, computationally efficient spatial contrast enhancement method which performs enhancement by considering the spatial locations of gray-levels of an image instead of direct use of gray-levels or their co-occurrences. Contrast enhancement is the important factor in image enhancement. Contrast enhancement is used to increase the contrast of an image with low dynamic range and bring out the image details that would be hidden. The enhanced image is looks qualitatively better than the original image if the gray-level differences. This work proposes a novel algorithm, which enhances the low contrast input image by using the spatial information of pixels. This algorithm introduces new method to compute spatial entropy of pixels using spatial distribution of gray levels. This is different than the conventional methods, this algorithm considers the distribution of spatial locations of gray levels of an image instead of gray level distribution or joint statistics computed from gray levels of an image. For each gray level the corresponding spatial distribution is computed by considering spatial location of all pixels having the same gray level in histogram. From the spatial distribution of gray levels of an image entropy can be measured and create distribution which can be further mapped to uniform distribution function to achieve final contrast enhancement. This method achieves contrast enhancement of low contrast image without altering the image if the image's contrast is high enough. This algorithm considers transform domain coefficient weighting to achieve global and local contrast enhancement of the image. Experimental results show that proposed algorithm produces better enhanced images than existing algorithms.**

***Keywords: Contrast enhancement, spatial entropy, image quality enhancement, SECE, QRCM, RMSE, CSIQ.***

## I INTRODUCTION

The process of partitioning a digital image into multiple regions (set of pixel) is called image segmentation. Segmentation of an image entails the division or separation of the image into regions of similar attribute.

The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide better input for other automated image processing techniques.Image Enhancement (IE) transforms images to provide better representation of the subtle details. It is an indispensable tool for researchers in a wide variety of fields including (but not limited to) medical imaging, art studies, forensics and atmospheric sciences. It is application specific: an IE technique suitable for one problem might be inadequate for another. For example forensic images or videos employ techniques that resolve the problem of low resolution and motion blur while medical imaging benefits more from increased contrast and sharpness. Thus, for example, a method that is quite useful for enhancing X-ray images may not be the best approach for enhancing satellite images taken in the infrared band of the electromagnetic spectrum. There is no general theory of image enhancement. When an image is processed for visual interpretation, the viewer is the ultimate judge of how well a particular method works.

## II PROBLEM DEFINITION

Producing digital images with good brightness/contrast and detail is a strong requirement in several areas like vision, remote sensing, biomedical image analysis, fault detection. Producing visually natural images or transforming the image such as to enhance the visual information within, is a primary requirement for almost all vision and image processing tasks. Methods that implement such transformations are called image enhancement techniques.

**Figure 1a: Original Image** **1b. Enhanced Image**

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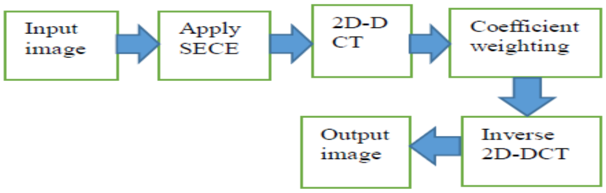


**Figure 2: Block diagram of SECEDCT algorithm.**

The implementing algorithm is named as "Spatial Entropy based Contrast Enhancement in DCT (SECEDCT)" which is generalization of SECE which perform both global and local contrast enhancement of image. SECE produces global contrast enhancement of an input image without altering the processed histogram with respect to the original histogram. SECE produces the results of contrast enhanced image without any apparent distortion on it. To achieve both global and local contrast enhancement, transform the coefficients of globally enhanced image with SECE using 2D-DCT (2D discrete cosine transform). Further coefficient weighted and apply inverse 2D-DCT (2D inverse discrete cosine transform) to obtain output image which is contrast enhanced globally and locally.

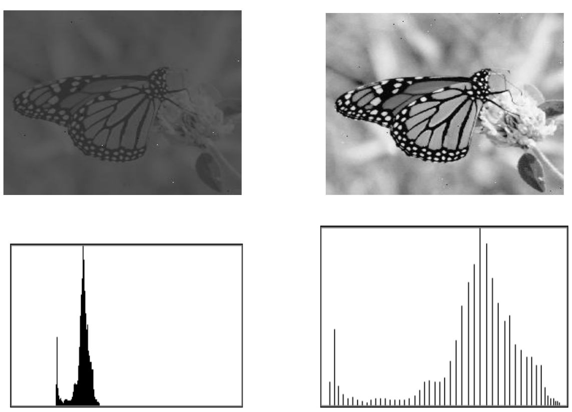

**Figure 3: Input Image & SECE Output Image**
Histograms of input & SECE enhanced output image

The following steps are followed enhancing of image by SECE

Step1: Input image can be resized and generate histogram of an image

Step2: Computation of spatial histogram of gray level of an image

Step3: Spatial entropy can be measured at each gray level and corresponding discrete function is evaluated at each gray level. Cumulative distribution function (CDF) is evaluated from discrete function.

Step4: Using CDF gray levels of input are mapped to output and generate output histogram in which all gray levels are distributed entire dynamic region by preserving the shape of the histogram.

## III IMPLEMENTATION

A parameterized global contrast enhancement is proposed The proposed algorithm is named as Spatial Mutual Information RANK(SMIRANK). One can extend SMIRANK to perform both global and local contrast enhancement at the same time using DCT domain coefficients manipulation as in SECEDCT or RSECEDCT. In order to quantify the level of contrast change between the original and processed images, this paper also proposes a new quality-aware relative contrast measure. A quality-aware relative contrast measure (QRCM) is proposed to assess the level of visual deformations on the output image.

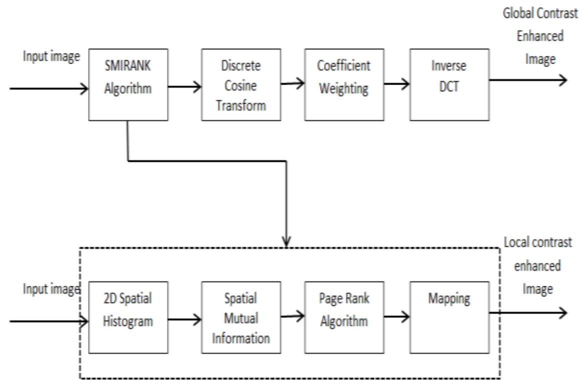


**Figure 4: Block diagram of proposed SMIRANK algorithm**

The performance of QRCM is evaluated on three aspects of its prediction power:
1) Prediction accuracy;
2) Prediction monotonicity; and
3) Prediction consistency.

## IV Algorithms Implementation

We use standard natural test images from TID2013 dataset, RGB-NIR dataset , and CSIQ dataset for quantitative and qualitative evaluations. The TID2013 image dataset offers 25 reference images of which 24 are natural and 1 is synthetic. Contrast of each reference image is altered at5 different levels to produce 5 images: "Level 1" corresponds to a small contrast decreasing; "Level 2" corresponds to asmall contrast increasing; "Level 3" corresponds to a larger contrast decreasing; "Level 4" corresponds to a larger contrast increasing; and "Level 5" corresponds to the largest contrast decreasing . The RGB-NIR image dataset consists of 477 images in 9 categories captured in RGB and near-infrared (NIR). RGB images are employed in tests. Similar toTID2013, CSIQ image dataset offers 30 reference images. Contrast of each reference image is degraded at 5 consecutive levels for which "Level 5" corresponds to the largest contrast

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degrading.SMIRANK algorithm is compared with the conventional approaches such as GHE and SECE for performance enhancement appraisal. PLCC, SROCC and RMSE are measured as numerical parameters for performance evaluations. The obtained results are as shown below.

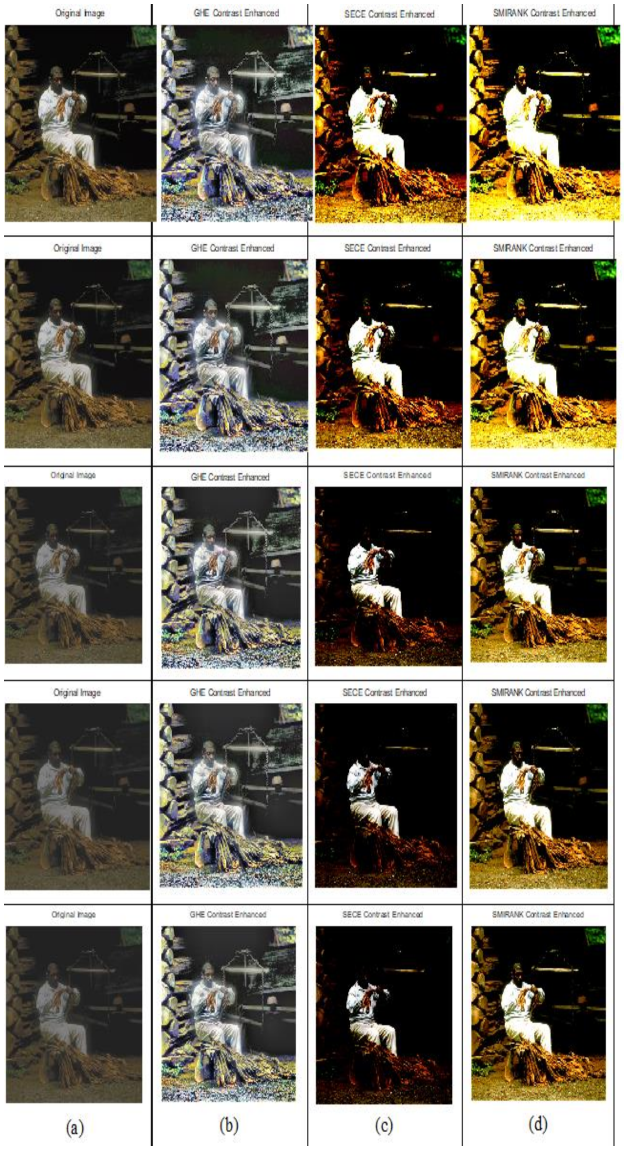


**Figure 5: Obtained results of 'Rope Image' from CSIQ dataset, Row-1: Level-1, Row-2: Level-2, Row-3: Level-3, Row-4: Level-4, Row-5: Level-5, (a) Original Image (b) GHE contrast Enhanced Image (c) SECE contrast Enhanced Image (d) SMIRANK contrast enhanced Image**

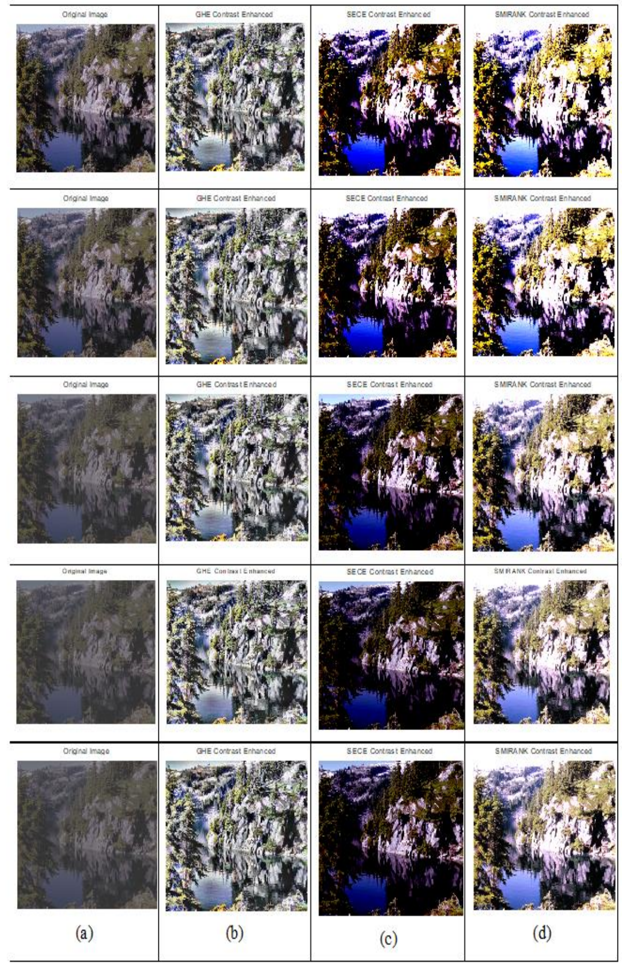


**Figure 6: Obtained results of 'Lake Image' from CSIQ dataset, Row-1: Level-1, Row-2: Level-2, Row-3: Level-3, Row-4: Level-4, Row-5: Level-5, (a) Original Image (b) GHE contrast Enhanced Image (c) SECE contrast Enhanced Image (d) SMIRANK contrast enhanced Image.**

## V RESULTS

Below Tables represents simulation results.

Table.1 Performance metrics for "Rope Image" from CSIQ database

| Level | Metric | GHE | SECE | SMIRANK |
|---|---|---|---|---|
| 1 | PLCC | 0.9074 | 0.9077 | 0.9117 |
| | SROCC | 0.8583 | 0.8584 | 0.8665 |
| | RMSE | 0.4622 | 0.4610 | 0.4589 |

| | | | | |
|---|---|---|---|---|
| 2 | PLCC | 0.9026 | 0.9093 | 0.9115 |
| | SROCC | 0.8598 | 0.8599 | 0.8660 |
| | RMSE | 0.4599 | 0.4563 | 0.4521 |
| 3 | PLCC | 0.9064 | 0.9049 | 0.9112 |
| | SROCC | 0.8574 | 0.8578 | 0.8664 |
| | RMSE | 0.4641 | 0.4631 | 0.4591 |
| 4 | PLCC | 0.9112 | 0.9118 | 0.9155 |
| | SROCC | 0.8595 | 0.8602 | 0.8669 |
| | RMSE | 0.4582 | 0.4553 | 0.4523 |
| 5 | PLCC | 0.9097 | 0.9054 | 0.9124 |
| | SROCC | 0.8616 | 0.8625 | 0.8666 |
| | RMSE | 0.4658 | 0.4652 | 0.4581 |

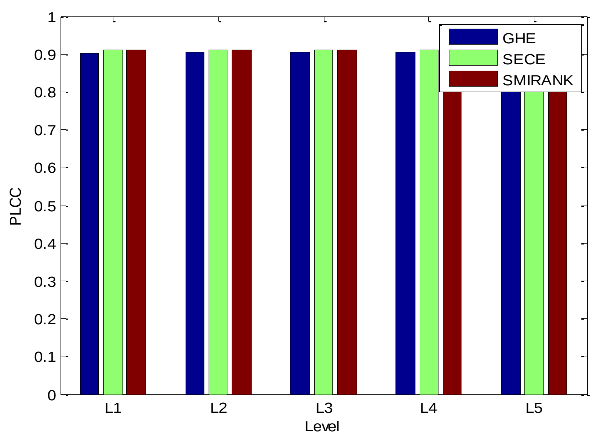


**Figure 7: PLCC comparative analysis for 'Rope Image'**

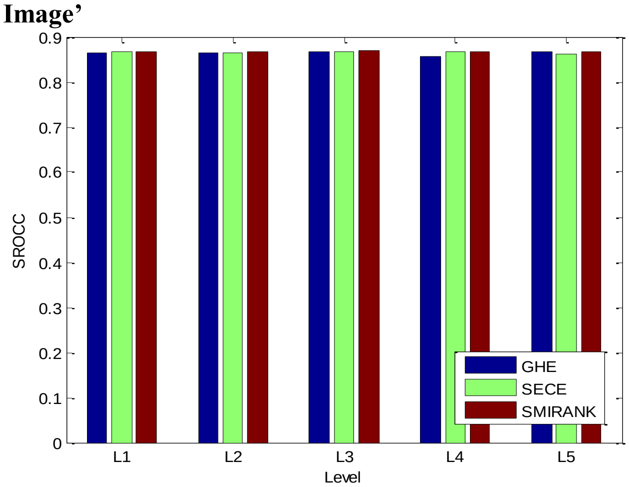


**Figure 8: SROCC comparative analysis for 'Rope Image'**

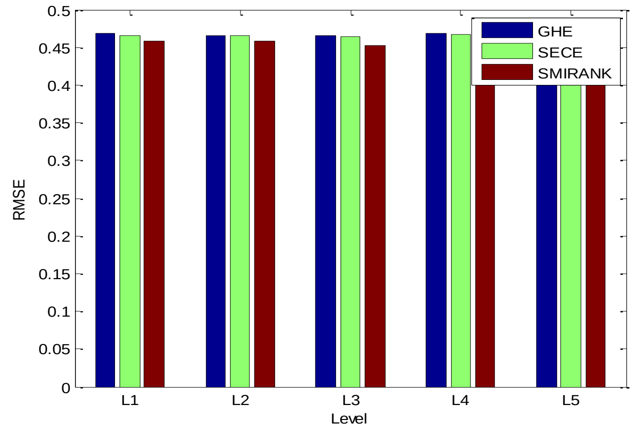


**Figure 9: RMSE comparative analysis for 'Rope Image'**

Table.2: Performance metrics for "Lake Image" from CSIQ database

| Level | Metric | GHE | SECE | SMIRANK |
|---|---|---|---|---|
| 1 | PLCC | 0.9058 | 0.9097 | 0.9111 |
| | SROCC | 0.8576 | 0.8635 | 0.8678 |
| | RMSE | 0.4582 | 0.4566 | 0.4522 |
| 2 | PLCC | 0.9019 | 0.9017 | 0.9119 |
| | SROCC | 0.8593 | 0.8612 | 0.8674 |
| | RMSE | 0.4608 | 0.4599 | 0.4587 |
| 3 | PLCC | 0.9076 | 0.9090 | 0.9126 |
| | SROCC | 0.8652 | 0.8691 | 0.8699 |
| | RMSE | 0.4762 | 0.4758 | 0.4644 |
| 4 | PLCC | 0.9066 | 0.9124 | 0.9158 |
| | SROCC | 0.8614 | 0.8652 | 0.8698 |
| | RMSE | 0.4680 | 0.4613 | 0.4514 |
| 5 | PLCC | 0.9072 | 0.9113 | 0.9163 |
| | SROCC | 0.8594 | 0.8599 | 0.8698 |
| | RMSE | 0.4675 | 0.4688 | 0.4697 |

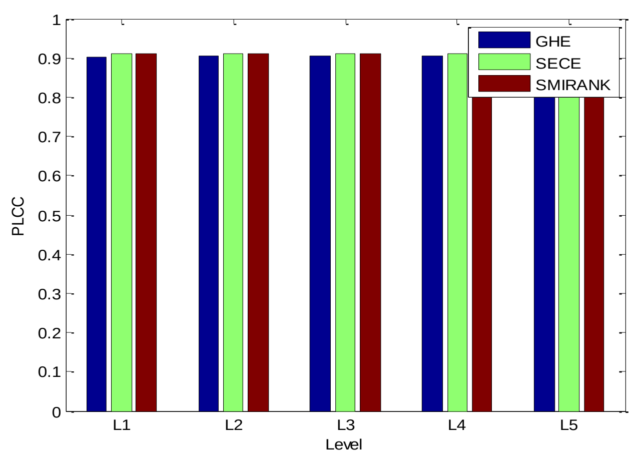


**Figure 10: PLCC comparative analysis for 'Lake Image'**

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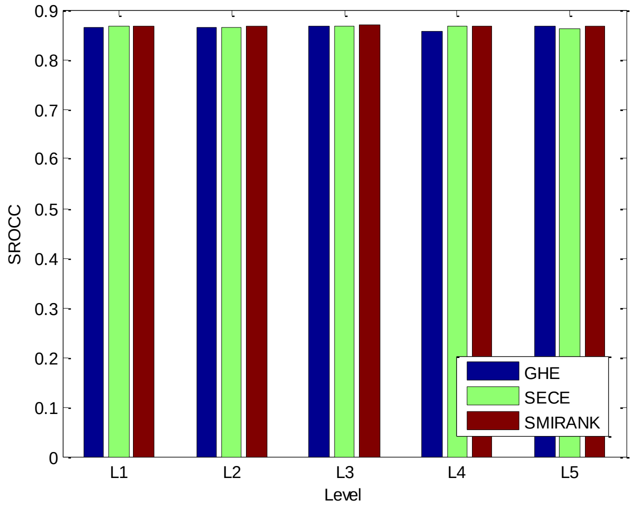


**Figure 11: SROCC comparative analysis for ' Lakee Image'**

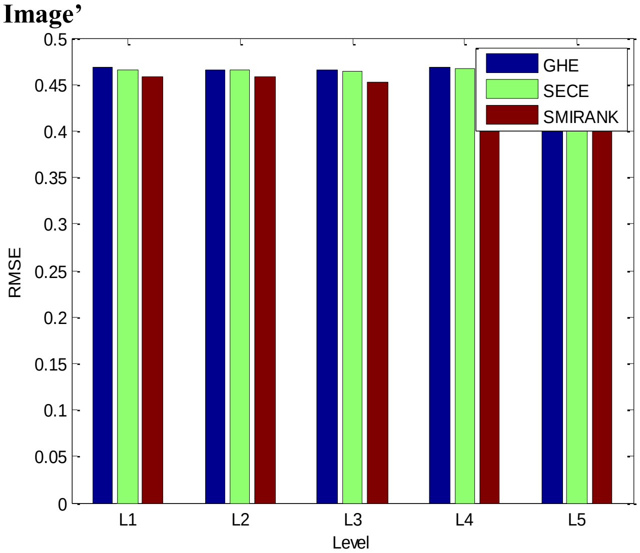


**Figure 12: RMSE comparative analysis for 'Lake Image'.**

| Metric | PLCC | SROCC | KROCC | RMSE | MAE |
|---|---|---|---|---|---|
| PSNR | 0.8226 | 0.8400 | 0.6393 | 1.4794 | 1.1830 |
| SSIM | 0.7656 | 0.7777 | 0.5796 | 1.6737 | 1.2810 |
| VSNR | 0.8287 | 0.8368 | 0.6357 | 1.4560 | 1.1520 |
| IFC | 0.5104 | 0.7423 | 0.5495 | 2.2376 | 1.8331 |
| MSSIM | 0.8666 | 0.8762 | 0.6852 | 1.2983 | 1.0188 |
| VIF | 0.7983 | 0.7933 | 0.5999 | 1.5668 | 1.2240 |
| UQI | 0.7537 | 0.7564 | 0.5595 | 1.7099 | 1.3066 |
| Ours | 0.8909 | 0.8979 | 0.7095 | 1.1816 | 0.9245 |

**Figure 13: Existing System Results.**

| Level | Metric | GHE | SECE | SMIRANK |
|---|---|---|---|---|
| 1 | PLCC | 0.9058 | 0.9097 | 0.9111 |
| | SROCC | 0.8576 | 0.8635 | 0.8678 |
| | RMSE | 0.4582 | 0.4566 | 0.4522 |
| 2 | PLCC | 0.9019 | 0.9017 | 0.9119 |
| | SROCC | 0.8593 | 0.8612 | 0.8674 |
| | RMSE | 0.4608 | 0.4599 | 0.4587 |
| 3 | PLCC | 0.9076 | 0.9090 | 0.9126 |
| | SROCC | 0.8652 | 0.8691 | 0.8699 |
| | RMSE | 0.4762 | 0.4758 | 0.4644 |
| 4 | PLCC | 0.9066 | 0.9124 | 0.9158 |
| | SROCC | 0.8614 | 0.8652 | 0.8698 |
| | RMSE | 0.4680 | 0.4613 | 0.4514 |
| 5 | PLCC | 0.9072 | 0.9113 | 0.9163 |
| | SROCC | 0.8594 | 0.8599 | 0.8698 |
| | RMSE | 0.4675 | 0.4688 | 0.4697 |

**Figure 14: Proposed System Results**

## VI CONCLUSIONS

In this work global contrast enhancement using PLCC, SROCC, RMSE algorithms are implemented. The characteristics and performance of the existing methods are analyzed and summarized, and the shortcomings of the present work in this field are further revealed. The essential purpose of low-light image enhancement is to improve the image contrast both globally and locally in a certain range of the gray space in accordance with the distribution of the gray values of the original image pixels. The Pearson correlation coefficient describes how strong the relationship between subjective MOS and evaluated objective scores is. The value lies between -1 and 1. The Spearman rank-order correlation coefficient (SROCC) is a nonparametric measure of rank correlation. It assesses how well the relationship between two variables can be described using a monotonic function. The difference between PLCC and SROCC is that the former only assesses linear relationships whereas the latter assesses monotonic relationships that may or may not be linear. Root-mean-square error (RMSE) is the most widely used performance evaluation measure and it computes the prediction error.

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