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INSTINCTIVE FEATURE FUSION PERFORMANCES FOR AESTHETIC ANALYSIS OF INTERPLANETARY AND TERRAIN IMAGES

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ABSTRACT

This is a presentation of a perceptually calibrated system for automatic aesthetic evaluation of interplanetary and terrain images. The work is built upon the concepts of reference image quality assessment, the focus being on the main difference on rating the image aesthetic attributes. In contrast to the recent attempts on the highly subjective aesthetic judgment problems such as binary aesthetic ratings, the method aims on providing a reliable objective basis of comparison between aesthetic properties of different photographs. With this our system computes perceptually calibrated ratings for a set of fundamental and meaningful aesthetic attributes of an image. The input of fusion techniques can enhance the quality and clarity of the aesthetic images. It can be used for the improvisation on the current state of the art in automatic aesthetic judgment and enable the interesting new photo on interplanetary and terrain images evaluation and providing aesthetic analysis and feedback.

Keywords—Aesthetic fusion, aesthetic evaluation, aesthetic analysis, aesthetic ratings.

I. INTRODUCTION

The Current developments in image procurement and visual computing made technology cheaper and effortlessly available, consequently putting more power into the hands of an average user. High quality cameras, standalone or integrated into mobile devices, as well as advanced image editing tools are more commonly used than ever. From the user's point of view, these new technologies create the expectation of more appealing images. But obtaining attractive results requires not only advanced tools, but also the knowledge and execution of basic aesthetic philosophies during acquisition and excision. The problem is that the average user does not always have the necessary training and experience, nor the interest in acquiring them. Thus, demonstrating aesthetic principles and building systems that give instinctive aesthetic feedback is a research area with high practical significance.

The interest in obtaining aesthetically pleasing results with minimal effort is evident from the fact that simple and effective photo editing tools like Instagram are very popular among casual snappers. Similarly, Fujifilm's Image Intelligence framework that exploits multiple systems (such as light source recognition, face detection, etc.) to improve image aesthetics, Sony's Party-shot™ technology where a revolving platform adjusts the camera for best photographic configuration, and the Smile Shutter™ where the camera releases the shutter when people smile, are all examples for incorporation of models of basic photographic principles with the current imaging technologies. These developments in the industry are also paralleled by the research community with the recently increasing amount of publications on twofold classification of image sets into aesthetically appealing or not, and automatic aesthetic judgment by predicting an overall aesthetic rating.

In automatic aesthetic decision is useful for many practical purposes, such decisions the in form of a yes/no answer, or a percentage score do not explain why the evaluated image is aesthetically pleasing or not. This is because when designing such systems, understandably the image features are selected based on their classification performance of overall aesthetics, but not automatically on how well they correlate with the aesthetic characteristics they entitlement to evaluate. As an example, it is often not discoursed if a "clarity" feature actually corresponds to what people consider as the photographic clarity rule, or is some abstract heuristic that happened to result in accurate arrangement. While this approach is perfectly fine for predicting a single-dimensional outcome, a multidimensional aesthetic analysis based on ratings of expressive aesthetic characteristics requires a different approach and poses additional challenges.

We can trust the first face is detection a set of image individuality that are simple enough to be articulated as computer programs, but at the same time are intimately related to some essential photographic features. Once these characteristics are defined, another challenge is designing and executing a subjective study through which one can consistently regulate ground truth characteristics ratings on a set of real world images. Once the independent data is found, the final challenge is the strategy, operation and standardization of metrics that expect a rating for each aesthetic characteristic.

In the current work we test these challenges and present a system that calculates an aesthetic monogram from a single image that encompasses calibrated ratings of expressive aesthetic characteristics and delivers an objective basis for aesthetic evaluation (Figure 1).In the paper we present these aesthetic features (Section 3), discuss the new process through which we obtain individual evaluations for each aesthetic features, and propose metrics that predict aesthetic features ratings and calibrate them using subjective data. We also present exemplary applications of our system to automated aesthetic analysis, HDR tone mapping evaluation, and multiscale contrast editing .

In the next section we review the previous work on automated image aesthetics, image quality assessment and subjective evaluation of high level visual features. We also briefly discuss the general limits and scope of computational aesthetic judgment.

II. Related Work

There are numerous sources on the basic strategies of photography (refer to Freelan's work [1] as an example). These publications often describe a set of photographic principles that should be taken into reflection for shooting aesthetically pleasing photographs. At a high level, the task of the photographer can be seen as assessing the shot in terms of these photographic principles and seeking the optimum balance between different aesthetic features that leads to an aesthetically pleasing result.

Computational aesthetic decision methods follow a workflow similar to the photographer's. Aesthetic judgment has often been approached as a learning problem on image features obtained from a large set of images (see Savakis et al. [2], Datta et al. [3] and Joshi et al. [4] for an overview), where the task is a binary classification between aesthetically pleasing and not pleasing images. Datta, et al. [5] proposed a linear SVM classifier that uses 15 image features selected among the initially suggested 56 features based on classification performance. A similar approach for video has been presented by Moorthy et al. [6]. Ke et al. [7] proposed using image features based on common-sense photography and utilize a na¨ıve Bayes classifier based on their observation that the interactions between the aesthetic features are not linear. The two-fold organization accuracy of all these approaches on subjective data is in the 70% range. More recent work along these lines evaluated the use of generic image descriptors for aesthetic quality valuation [8]. Luo and Tang [9] reported a significant upgrading in accuracy by extracting a rectangular image window that comprises most of the high frequency details, and framing features that take into account this two-fold segmentation. Other work in this area includes [10], [11], [12], [13]. Similarly, segmentation using a saliency map [14] and face detection [15] has been explored in the context of automated image aesthetics. Unlike the binary classification methods, acquire is a general online aesthetic rating engine [16] that predicts an overall aesthetic percentage rating. Recent work has also been focused on more specific sub-problems such as photographic configuration [17], [18], [19], [20], view endorsement [21], color compatibility [22], [23], [24], and candid portrait selection from videos [25], as well as the use of more specialized features like sky-illumination features and object types in the scene [26]. Finally, a large data set with associated meta-data has been published to facilitate further image aesthetics research. [27] Our work takes inspiration from the great body of previous work in this area, with the main difference being our emphasis on the aesthetic *signature* concept.

Fig. 1. A comparison of the aesthetic signatures reveals that the editing greatly enhanced tone and depth of the under-exposed original image at the cost of slight decreases in sharpness and clarity. Images courtesy of Wojciech Jarosz.

Image excellence assessment methods seek to estimate "image quality" without requiring user involvement. Given a test image with some inadequacies, quality is either defined as the fidelity to a reference image [28], [29], or by the absence of certain types of distortions such as compression, ringing [30], blur [31], and banding [32]. The latter, no-reference type of quality assessment is significantly more challenging because such quality metrics do not utilize a reference image, but instead rely on their internal model of alterations. There have been also some attempts on building more general no-reference metrics by combining the individual contribution of image features and distortions [33], as well as utilizing natural image statistics [34]. An interesting recent work on image completion combines ideas from image aesthetics and quality prediction [35]. At a conceptual level, our method is influenced by such generalized no-reference quality assessment methods. However, our work is fundamentally different in that our metrics predict the magnitude of a set of aesthetic features instead of predicting the visibility of distortions. Moreover, as its outcome our method provides a basis for aesthetic analysis rather than assessing image quality.

Individual evaluation of visual features has been performed through psychophysical experiments with the goal of determining a mapping from objectively computable values to perceptually expressive units. A classic example is Whittle's luminance difference discrimination experiment [36] that reveals the nonlinear perception of luminance contrast. More recently, similar experimental methods have been used to originate models of "visual equivalence" of substances with different material belongings, geometry and illumination [37], the discriminability of aggregates of objects [38], the effects of global brightness approximations on material appearance [39] among others. Our new method is analogous to this line of research, in that we investigate the perception of aesthetic features and seek to design and calibrate metrics whose expectations match individual ground truth ratings.

The scope of our model is limited to the "generalist" part of aesthetic judgment. More specifically, Immanuel Kant asserts two necessary belongings of an aesthetic judgment :(1) subjectivity (being based on a feeling of pleasure and displeasure, rather than being empirical), and (2) universality (involving an expectation or claiming on the agreement of others) [40]. The contradicting nature of these properties lead to the "Big Question" of aesthetics: whether it is even possible for a subjective judgment to be universal [41]. The big question is the subject of an ongoing debate, where the generalist view holds that there exist general reasons for aesthetic judgments, and the particularist view denies that aesthetic judgments rely on general reasons.

In the practice appears to be somewhere between both views: "each to their own taste" does apply to aesthetic decisions, but there is also a notable degree of agreement between decisions of different people in support of the generalist view. Subscribing to the generalist view enables a computational model of image aesthetics, but also draws the limits of such a model by ignoring artistic intention as well as previous knowledge and contextual information (Figure 2). Especially for the ultimate goal of correctly predicting a numeric overall aesthetic rating, this inherent limitation of automated image aesthetics poses an obstacle. Consequently, while we show that our method performs better than the state-of-the-art in predicting an overall aesthetics rating (Section 5.4), the focus of this work is on the design, computation and calibration of a meaningful aesthetic signature that summarizes representative photographic properties of an image.

III. AESTHETIC FEATURESS

One of the main challenges of automated image aesthetics is identifying a set of aesthetic features that can be expressed algorithmically, and are closely related to photographic principles they claim to model. Since it is practically impossible that a computational system accounts for every photographic rule, one needs to determine some guidelines for choosing some aesthetic features over others. In this work, we considered the following criteria while determining the set of aesthetic features:

- **Generality:** while sharpness is relevant in every photograph, a more specific features such as facial expression is only useful for photographs with people. We chose not to limit our work to a specific type of photographs, and accordingly we selected among the more general features.
- **Relation to photographic rules:** from a modeling point of view it may be desirable that the aesthetic features are orthogonal to each other. However this would also require to invent new, artificial features that are not necessarily meaningful to humans, since in reality the photographic rules are not always orthogonal. In this work our main goal was to compute a multidimensional human interpretable aesthetic signature, and accordingly we chose to closely follow the photographic rules at the cost of possibly correlated features.
- **Clear definition:** in photography literature photographic rules and practices are often communicated through examples rather than mathematical formulas or concrete statements. For the purpose of automating image aesthetics we selected features that can be defined as clearly as possible.

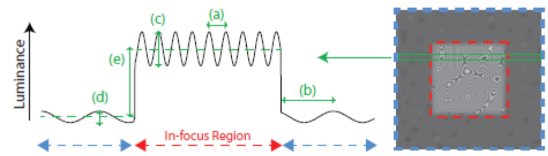

Fig. 2. From photographic rules to concretely defined aesthetic attributes: the 1D luminance (left) obtained by taking a slice from an abstract image (right) is used to build an intuition on how to express photographic rules in computational terms.

Fig. 3. A contrast among a sharp (left) and out-of-focus (right) photograph. Photographs courtesy of Muhammad Mahdi Karim.

In the rest of this section we discuss the photographic rules selected based on the above principles that form the foundation of the aesthetic features we use in our system. Using the 1D luminance profile in Figure 2-left obtained from the abstract image (right), we also investigate each rule in image processing terms to form a basis for our discussion in the later stages. During our discussion of each photographic rule we highlight the relevant image features such as the spatial frequency of the in-focus region (a) and the background (b), the contrast magnitude of the in-focus region (c) and the background (d), and the luminance difference between the two regions (e) as depicted in Figure 2-left. The aesthetic features we discuss do not cover all aspects of image aesthetics, but are still expressive enough to enable multiple novel applications. Moreover our framework can possibly be extended with other aesthetic features by following the workflow discussed previously.

In photography often times the camera is either focused to the entire scene, or to some specific scene object. An important rule of photography is ensuring that the in-focus region is sharp (Figure 3-left). Pictures with no scene elements in focus are often conceived as photographic errors. In fact, sharpening the in-focus region or the entire image is one of the very common post-processing operations to correct out-of-focus photographs, or to enhance the aesthetic quality of already sharp pictures. Sharpness is related to the magnitude and frequency of the image contrast within the in-focus region.

In addition to these features, the chromatic information of the image also plays an important role in image aesthetics. The colorfulness features can be used to differentiate photographs with lively and saturated colors from photographs with desaturated colors.

During our discussion we indicate the usually preferred directions the photographic rules, but we refrain from making any general statements on how each rule affects the overall aesthetics rating of an image. Due to the “particularistic” aspects of the aesthetic judgment process it is not uncommon that photographs not conforming to one or more of these rules are found aesthetically pleasing by the majority. In the figure right shows such an example that definitely violates the clarity rule, but in terms of overall aesthetics is still ranked among the highest in the photo.net dataset [3]. The next section discusses a subjective study where we obtained ground truth ratings for each aesthetic feature. The ground truth data is later used to design and calibrate the aesthetic features metrics presented in Section 5.2.

IV. SUBJECTIVE RATING STUDY

In this section we present an experiment where we obtained subjective ratings for the aesthetic features on a set of real world images. Using this subjective data we designed and calibrated the aesthetic features metrics we describe in the next section.

Experiment During our experiment the subjects were seated comfortably in front of two computer displays at a distance of approximately 0.5 meters. One of the displays showed a photographic image from our test set, whereas the other display is a simple stimuli and a short task description. The task consisted of rating single aesthetic characteristics of the photographic image among sharpness, depth, clarity, tone and colorfulness on a 5-point scale. The simple stimuli generated separately for each aesthetic feature were used to assist the subject by providing a neutral basis for each point of the rating scale.

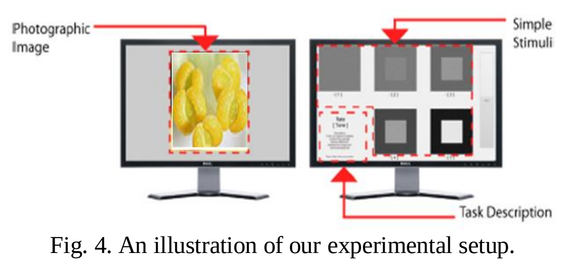

Fig. 4. An illustration of our experimental setup.

Stimuli We assembled a test set that comprised 20 different images per aesthetic features, all obtained from the photo.net data set where each image had an overall aesthetic rating assigned by a community of semi-professional photographers (refer to Datta etal. [3] for an analysis of the images and ratings). The images used in our experiment were manually selected with an effort to maximize the diversity of the features ratings as well as the overall aesthetic ratings.

A common problem of subjective rating experiments in the absence of a reference is that the subject has often no baseline for assessing the measured effect. This often causes the earlier subjective responses to be unreliable until the subjects see the more extreme cases in the experimental test set, and use those as anchor points for their judgment during the remaining trials. While as a counter-measure such experiments are often preceded by a short training session, especially for highly subjective tasks as ours, it is highly desirable to additionally provide a baseline for rating without biasing the subject. This task is challenging, because one cannot simply use real world photographs that would represent each rating on the 5-point scale, since the contents of the chosen photographs could invoke different reactions in different subjects and introduce unforeseen biases to the subjective ratings. To prevent this, we generated a set of 5 abstract images (one for each point in the rating scale) per aesthetic features building upon the abstraction in Figure 2. Our experiment was still preceded by a conventional training session, but additionally we used the emotionally neutral simple stimuli as a baseline for rating at each trial of the subjective experiment. Despite the presence of the simple stimuli, our subjects were made clear to ultimately rely on their own understanding of each feature to prevent constraining their judgments.

The simple stimuli consisted of a square that region represents a foreground object, centered in a larger square that represents the background (Figure 9). A random texture pattern was generated separately for the foreground and the background using Perlin noise. The stimuli for sharpness and depth were generated by applying Gaussian blur to the foreground texture and background texture, respectively. The clarity stimuli varied in the difference in the contrast magnitude of the texture between the foreground and the background, whereas the tone stimuli varied in the intensity difference between both image regions. On the other hand, the colorfulness stimulus was generated by modulating the saturation and size of a rainbow pattern. For all aesthetic features, the simple stimuli were generated to provide 5 roughly visually equal steps within the whole range of possible magnitudes. Each time when the subjects were evaluating an image in terms of aesthetic features, the 5-level simple stimuli for the corresponding aesthetic features were presented on the side.

Procedure The photographs in our test set were presented in a random order. At each trial, the 21 subjects participated in our study were asked to rate a single aesthetic features of the presented image without any time constraints. All subjects had near-perfect or corrected eyesight and their ages ranged from 21 to 42. Were asked to rate the entire set, whereas the others rated either the test images for sharpness, clarity and colorfulness, or the test images for depth and tone. Each subject participated in a training session that preceded the experiment where they were briefed on the experiment and the aesthetic features.

The results of our study are summarized in Figure 11- left, where we show the median ratings and subjective variation for each test image and aesthetic features. The following section discusses the aesthetic features metrics we designed and calibrated using the subjective ground truth data obtained in this section.

V. DATA FUSION TECHNIQUES

Data fusion techniques combine data from different sources together. The main objective of employing fusion is to produce a fused result that provides the most detailed and reliable information possible. Fusing multiple information sources together also produces a more efficient representation of the data. AUG Signals has been involved in research and development in the area of data fusion for over a decade. The company has developed techniques in all three categories of data fusion: Pixel / Data level fusion, Feature level fusion and Decision level fusion. Pixel level fusion is the combination of the raw data from multiple source images into a single image. Feature level fusion requires the extraction of different features from the source data – before features are merged together[51]. Decision level fusion combines the results from multiple algorithms to yield a final fused decision. AUG Signals' fusion algorithms have been applied to various types of data including:

- Multi-sensor data,
- Multi-temporal data,
- Multi-resolution data
- Multi-parameter data.

The two main application areas are Image Fusion and Algorithm Fusion. Image Fusion techniques use different fusion techniques to combine multiple images into a single fused image[51]. Algorithm Fusion techniques fuse the decision results from multiple algorithms to yield a more accurate decision.

A. Image Fusion

Image Fusion produces a single image by combining information from a set of source images together, using pixel, and feature or decision level techniques. The fused image contains greater information content for the scene than any one of the individual image sources alone [52]. The reliability and overall detail of the image is increased, because of the addition of analogous and complementary information. Image fusion requires that images be registered first before they are fused. Image fusion of multi-temporal and multi-sensor images is of considerable importance to earth and space observation applications, such as environmental, agricultural and maritime monitoring. Satellites sensors alone often cannot offer the necessary spatial resolution required for certain applications. Fusion of multiple temporal satellite images is used for resolution enhancement, creating a single high-resolution image. Depending on the number of input images, the resolution can be enhanced 2 to 5 times using fusion algorithms. In a multi-sensor environment, pixel level fusion can generate a fused image that provides the best description of a scene. Each sensor provides complementary information that can be combined together into a fused image. Fused images can be used by other algorithms for further processing, such as for target detection or tracking. Fused images are also ideal for human end users, who cannot easily visualize and combine the results from multiple sensors.

The Image Fusion Toolbox developed by AUG Signals, currently available for MATLAB and IDL, contains different image fusion algorithms[52]. This includes well-known approaches and unique and innovative algorithms developed by AUG Signals. The following is a selected list of algorithms provided by the toolbox:

- Statistical Methods
- Markov Random Fields
- Dempster-Shafer Theory
- Neural Networks
- Fuzzy Logic
- Wavelets
- Super-resolution
- AUG Signals' Super-resolution

AUG Signals' Image Fusion Toolbox, along with the Image Registration and the Blur Estimation, Restoration and Speckle Reduction tools, form the AUG Signals' Image Processing Suite, which is accessible under one easy to use, yet highly configurable Graphical User Interface[53]. It provides effective tools to:

- Generate an enhanced spatial resolution image using registered spatio-temporal images with minimal misregistration errors.
- Eliminate deterministic blurs that are introduced with the spatial resolution improvements in the image and avoid singularity and regularization artifacts.
- Estimate and reduce additive and multiplicative image noise using optimal statistical criteria.
- Eliminate blurs introduced by the sensors or atmosphere without introducing artifacts.

The figure below shows the Mat lab user interface for the Image Fusion Toolbox. Two examples follow, demonstrating the applications of fusion algorithms.

Example 1: *Image Fusion for AVIRIS and RADARSAT data the two input images are from two different sensors: AVIRIS and RADARSAT. Although they depict the same region, each image contains complementary information. The fused image combines the details from both images.*

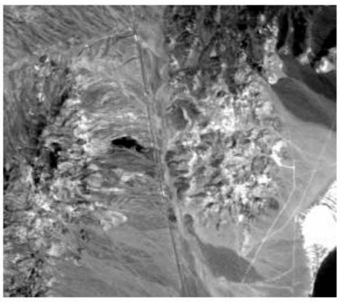

Fig 5. AVIRIS image (band 183)

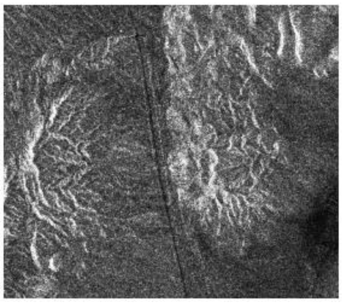

Fig 6. High resolution RADARSAT Image

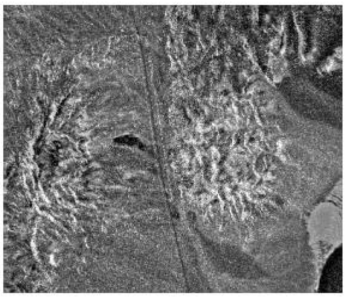

Fig 7. The fused image, using the Shift Invariant Wavelet Transform Method

Example 2: *Image Fusion for Target Enhancement (Landsat TM) This example shows how targets in one image can be fused into another image that is the frame of reference.*

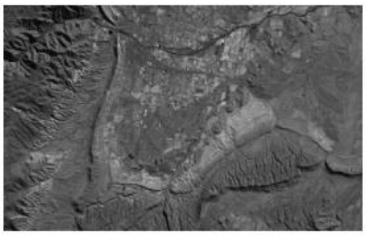

Fig 8. Frame of reference

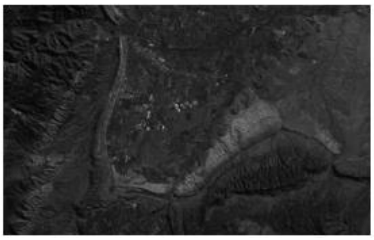

Fig 9. Image with targets

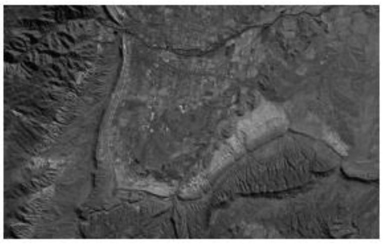

Fig.10. Fused image with enhanced Targets

B. Algorithm Fusion

Algorithm fusion is an unique research area in which AUG Signals has been heavily involved. Algorithm fusion uses sophisticated rules to combine decisions from multiple algorithms into a final decision, increasing the overall performance of the system. Two Algorithm Fusion techniques are discussed below, Multi-CFAR Detection and Decision Fusion of Separate Data-mining Subsystems on Multiple Data Sources.

Multi-CFAR Detection: Unlike single CFAR detectors, AUG Signals' Multi-CFAR detector uses several CFAR detectors, such as the Ordered Statistics (OS) CFAR detector and the Cell Averaging (CA) CFAR detector, to perform detection on the same data[54]. The detection decisions from each detector are fused using specific rules to obtain a final detection decision. The combination of CFAR detectors is able to provide complementary information and achieve higher detection performance than any single detector, while maintaining a constant false alarm rate. Please see AUG Signals' Technical Brief on CFAR Detection for more details.

Decision Fusion of Separate Data-mining Subsystems on Multiple Data Sources the aim of fusing the decisions of separate data-mining subsystems operating on separate data sources is to increase the overall performance. Decision level fusion was chosen against data fusion and feature fusion in the three-level fusion hierarchy, because of its feasibility, lower computational complexity and robustness to the removal or addition of individual data sources[55]. Decision fusion is the major component in the multi-source data-mining system developed by AUG Signals for decision support and situation assessment. It is able to automatically generate a solution. It is able to automatically generate a solution given a library of features, data-mining algorithms and fusion techniques that are comparable to a tuned solution for the data set. The advantages of this system are its ability to incorporate:

- Multiple-source (sensor) data
- Multiple similar and dissimilar features
- Multiple data-mining algorithms

- Multiple fusion methodologies

This produces a system that exploits the resources of truth data, feature extraction, data-mining and fusion, while minimizing the level of expertise required for the end-user. The architecture for the system is shown on the following page.

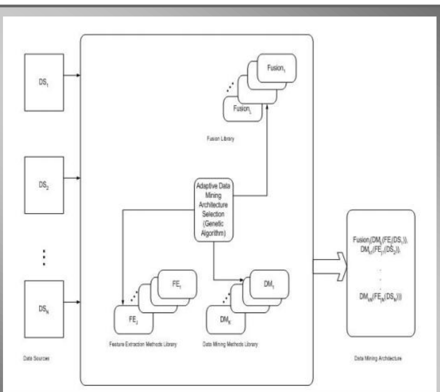

Fig 11. Multiple Source Data-mining Architecture

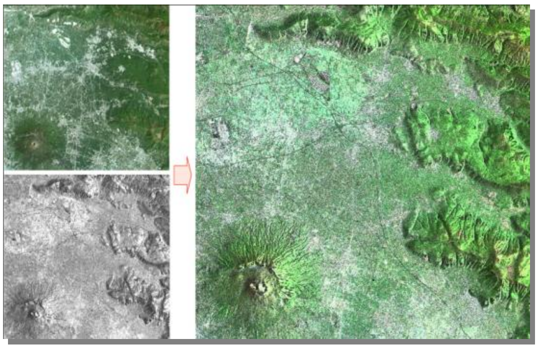

Fig 12. Shows two interplanetary aesthetic image are been fused and displaying the result

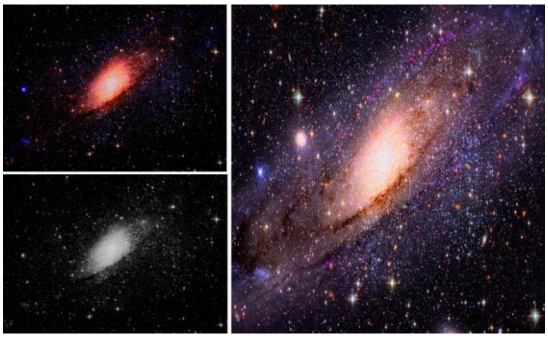

Fig 13. Shows two terrain aesthetic image are been fused and displaying the result

The fig12 and fig.13 showed some sampled output of interplanetary and terrain images, where two aesthetic images are fused to form a good clarity feedback images.

VI. CONCLUSION

In this work it has been presented a frame work for automated image aesthetics that can be utilized in current photo editing software packages for providing aesthetic guidance to the user. Given two images, the system automatically computes the aesthetic fusion that comprises calibrated ratings of a set of aesthetic attributes, and provides a compact representation of some of the input image's fundamental photographic properties. The experimental procedure has been described for obtaining subjective ratings for each aesthetic attribute, and presented a set of metrics capable of accurately predicting these subjective ratings. It has been showed that the method outperforms the current state of art in predicting an overall aesthetics rating, as well as interplanetary and terrain application areas.

The aim was to enable the evaluation of all types of interplanetary and terrain images without any constraints on their content and aesthetic characteristics, and the aesthetic attributes that has been utilized in this work were chosen accordingly. Consequently the method is not limited to the expressiveness of the attributes that has to be evaluated. While it has been showed that the current system enables space and terrain applications, the aesthetic fusion techniques can still be enhanced by increasing its number of dimensions. Also, the aesthetic attribute metrics in this system trade off the generality, as we did not want the metrics to over fit the subjective dataset, but rather to capture consistently present tendencies of satellite images. The choice of this design also resulted in a slightly higher deviation of the metric predictions from subjective ground truth data than what would have been achieved with more complex metrics.

Since automated image aesthetics is fundamental to many visual computing methods, future directions for our work include in-depth treatment of satellite application areas enabled by this method, such as the ones demonstrated in the above mentioned output. Another direction could be specializing the method by taking into account further, more specific aesthetic attributes like the expressions of different species, the position of the horizon line, rule of the thirds, etc., that are only meaningful for certain types of photographs. Since in this work the reference data consists solely of real world images, another immediate future direction is testing to what extent our framework generalizes to synthetic images. It is also an interesting research question if there is a connection between recent work on image memo ability and aesthetics.

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