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An Overview of Color Constancy Algorithms

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Abstract

Color constancy is one of the important research areas with a wide range of applications in the fields of color image processing and computer vision. One such application is video tracking. Color is used as one of the salient features and its robustness to illumination variation is essential to the adaptability of video tracking algorithms. Color constancy can be applied to discount the influence of changing illuminations. In this paper, we present a review of established color constancy approaches. We also investigate whether these approaches in their present form of implementation can be applied to the video tracking problem. The approaches are grouped into two categories, namely, Pre-Calibrated and Data-driven approaches. The paper also talks about the ill-posedness of the color constancy problem, implementation assumptions of color constancy approaches, and problem statement for tracking. Publications on video tracking algorithms involving color correction or color compensation techniques are not included in this review.

Keywords: Color constancy, Categorization of algorithms, Video tracking.

1. Introduction

Over decades, researchers have tried to solve the problem of color constancy by proposing a number of algorithmic and instrumentation approaches. Nevertheless, no unique solution has been identified. Given a wide range of computer vision applications that require color constancy, it is not possible to obtain a unique solution. This led researchers in the field to identify sets of possible approaches that can be applied to particular problems. Particularly, efforts are directed towards identifying color constancy approaches that can be applied to real time video tracking as reviewd in this paper.

We present a simple example, which will give an insight into the problem of color constancy. Imagine, a light emitted by a lamp and reflected by a red color object, causing a color sensation in the brain of the observer. The physical composition of the reflected light depends on the color of the light source. However, this effect is compensated by the human vision system. Hence, regardless of the color of the light source, we will see the true red color of the object. The ability to correct color deviations caused by a difference in illumination as done by the human vision system is, known as *color constancy.* The same process is not trivial to machine vision systems in an unconstrained scene. This defines the

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color constancy problem. Therefore, the goal of color constancy research is to achieve an illuminant invariant description of a scene taken under illumination whose spectral characteristics are unknown (It is referred to as unknown illumination). It is a two step process. In the first step, an estimate of the illuminant parameters is obtained, and in the second step, the illuminant independent surface descriptor is parametrically computed [12, 33, 42]. Often illumination invariant descriptor of the scene are computed under an illumination whose spectral characteristics are known (It is referred to as canonical illumination)[24]. The choice of canonical illumination is somewhat arbitrary, but often this is the illumination for which the camera is balanced.

Mathematically, a color image is represented as,

$$E_k(x, y, \lambda) = \int_{\omega} R(x, y, \lambda) L(\lambda) S_k(\lambda) d\lambda \tag{1}$$

a product of three variables, namely, $R(x, y, \lambda)$ the surface reflectance, $L(\lambda)$ the illumination property, and $S_k(\lambda)$ the sensor characteristics, as a function of the wavelength λ, over the visible spectrum ω. The subscript k represents the sensor's response in the k^{th} channel and $E_k(x, y, \lambda)$ is the image corresponding to the k^{th} channel ($k = R, G, B$). If a constant surface reflectance and a known sensor characteristics are assumed, then any variation in illumination will change the color appearance of the image. In color constancy research, efforts are directed toward discounting the effect of illumination and obtaining a canonical color appearance.

The human vision system exhibits an approximate color constancy processing. The same phenomena cannot be observed in machine vision systems. The idea to obtain color constancy is based on many theories proposed by researchers in the field [10, 12, 13, 16, 18, 21, 24, 32, 40, 42, 52, 55]. Most of the theories identified color constancy as a very difficult and an under constrained problem. According to Hadamard [35], a French mathematician, a problem is well posed if the following three conditions are satisfied, (i) there exits a solution, (ii) this solution is unique, and (iii) this unique solution is stable. If any of these conditions are not satisfied, then the problem is known as ill-posed. In color constancy, the uniqueness and the stability of the solution cannot be guaranteed because of the high correlation between the color in the image and the color of the illuminant. This collinearity have the following effects on the estimation of illumination coefficients, (i) imprecise estimation and (ii) a slight variation is collinearity may lead to a large variation in the estimation.

A color applications such as video tracking is one of the active research fields in computer vision. It focuses on identifying a target (a person or an object) in an unconstrained environment. The tracking algorithm framework takes into consideration different features of the target like shape, size, orientation and color. From equation (1), we observe that a color image is a function of illumination. This makes the color feature more sensitive to changing environments and illumination conditions. Therefore, it is essentially important that color-based tracking algorithms be adaptive to color variations. Hence, it becomes utterly important to achieve approximate color constancy of the target to enhance the robustness of tracking

A color image is a function of three variables (equation(1)), therefore the assumptions are categorized into three classes, (i) assumptions based on sensors, (ii) assumptions based on surface reflectance, and (iii) assumptions based on illumination. Most cameras automatically perform a gamma correction, auto gain, white balancing and others, affect the image acquisition. Sensors automatically perform a gamma correction on the image and it is important to inverse the gamma correction to obtain the true RGB values of the image. In some literature, these RGB values are also referred to as raw values of the image. Barnard et al. [1] showed that the sensor factors can be normalized by careful camera calibration. Most of the theories assume Lambertian surfaces and diffuse reflection conditions [2, 3, 24], eventhough the occurrence of specular highlights have been of particular interest in the color constancy research. Specular highlights are understood to carry illuminant chromaticity information [16, 52, 55]. Some algorithms also assume spatially uniform illumination across the scene [2, 3, 21, 24], i.e., homogeneous illumination conditions. Such assumptions are void in unconstrained scenes. Researchers [8, 32, 36] have also addressed the issue of color constancy under inhomogeneous illumination conditions.

Besides these three general categories, assumptions about the diversity, and possible statistics of the surfaces and illuminants that will be encountered are also considered. The gray world (GW) algorithm [12] is based on the assumption that the color in each sensor channel averages to gray over the entire image. Any deviation from the gray value is due to the chromaticity shift of the illuminant. It is one of the important assumptions when trying to estimate the spectral distribution of the illuminant. Similarly, Scale by Max (SBM) algorithm provides the estimates of the illuminant by measuring the maximum response in each channel. SBM is also shown to be a subset of the Bayesian framework [49].

Barnard et al. [2, 3] provided a computational comparison between different color constancy algorithms. Those computational comparisons were obtained using a dataset [4] under constrained experimental conditions. The advantage of the dataset [4] is that the true spectral information of the illumination used to collect the data is known. This helps to compute the ground truth RGB and chromaticity values. The drawback of the dataset is that it does not model the illumination spectrum that will be observed in real practical images. We revisit most of the algorithms discussed in [2, 3] and also include reviews on the algorithms proposed until 2004.

We categorize the reviewed color constancy approaches into two categories and discuss them in detail in Section 2. In Section 3, the problem statement of video tracking is presented. We also discuss whether the algorithms of each categories can be applied to video tracking in their present form. Finally, conclusions and possible future works are presented in Section 4.

2. Color constancy algorithms

Researchers from various disciplines of engineering and science have tried to solve the color constancy problem. They proposed and applied many theories taking into consideration the assumptions and the sensor limitations. We categorizes methods into two main categories, namely, Pre-Calibrated approaches and Data-driven approaches. These categories are further subcategorized as shown below:

I. Pre-Calibrated approaches
   1. General transformation based approaches and
   2. Diagonal transformation based approaches.

II. Data-driven approaches
   1. Gray World and Scale By Max approaches,
   2. Retinex approaches,
   3. Gamut mapping approaches (may also be a diagonal approach),
   4. Statistical approaches, and
   5. Machine learning approaches.

2.1 Pre-Calibrated approaches

The sensor used to capture the color image is calibrated [1] and its response is studied under different illumination conditions. This is important for the selection of the canonical illumination. To obtain an illuminant invariant description of an image captured under unknown illumination conditions, transformation based approaches were introduced. These approaches map the surface reflectance observed under the canonical illuminant to the surface reflectance of the scene observed under unknown illuminant. They assume proper knowledge of the sensor characteristics and other assumptions such as uniform illumination and single illumination source. The linear (general) transformation and diagonal transformation approaches are discussed.

2.1.1 General transformation based approaches

In early 1980's transform based approaches were introduced. Most authors consider the transformation to be a linear map of 3 x 3 matrices. Gershon et al. [33] proposed an algorithm to solve for the transformation, based on three assumptions: (i) both the illumination and the surface reflectance spectra can be modeled using small dimensional basis sets, (ii) the average surface reflectance in every Mondrian patch is the same, and (iii) the illumination is uniform. The algorithm solved for the illuminant first and then estimated the transformation. However, the algorithm showed poor performance because the second assumption varied significantly and it is very difficult to always maintain uniform illumination. Maloney et al. [42, 43] proposed a 3-2 algorithm to solve for the limitations of [33] by modifying the assumptions. They made two further assumptions: (i) if there are n sensors, then the dimensionality of the illuminant is less than or equal to n and (ii) the illumination is locally uniform. These assumptions suggest that pseudo-inverse can be applied to solve for color constancy, if the surface reflectances are two dimensional. Unfortunately,the surface reflectances have higher dimension. Forsyth [24] extended [42, 43] these algorithms, MWEXT (Maloney-Wandell EXTension), to obtain a set of plausible mappings instead of a unique mapping.

2.1.2 Diagonal transformation based approaches

The color constancy algorithms in [21, 24, 36, 40, 49, 59] are based on diagonal matrix transformation. In this case, color constancy is obtained, by simply taking the dot product of diagonal matrix and the image matrix obtained under unknown illumination. This is equivalent to independently scaling each channel by a factor. West et al. [58] showed that von Kries hypothesis that chromatic adaptation is a central mechanism for color constancy is based on the diagonal matrix transformation. Barnard et al. [5] and Finlayson et al. [23], proposed a sensor sharpening method to improve the performance of the color constancy algorithms based on diagonal matrix transformation. The idea of sensor sharpening is to map the data by a linear transform into a new space where diagonal models are more reliable. The final result is then mapped back to the original RGB space by taking the inverse transformation. The performance of the color constancy algorithms depending on diagonal transformation is improved by spectral sharpening in terms of low root mean square error.

2.2 Data-driven approaches

The approaches discussed in this section evolve from a simple algorithmic implementation to the implementation of sophisticated statistical and machine learning algorithms to achieve color constancy.

2.2.1 Gray World and Scale by Max approaches

Gray World [12] and Scale by Max algorithms [2] are regarded as simple algorithms on the basis of simplicity of their implementation. They are still used as a benchmark for comparison when it comes to algorithmic approach to color constancy. The gray world algorithm is one of the oldest and the simplest color constancy algorithms. It is based on the assumption that the color in each sensor channel averages to gray over the entire image. The gray world algorithm estimate the deviation from the assumptions and is given by a simple expression,

$$l_r = mean(E_R),\ l_g = mean(E_G),\ l_b = mean(E_B) \tag{2}$$

where l_r, l_g, l_b are the mean value in each channel respectively and E_R, E_G, E_B are individual image channels.

In the scale by max algorithm, the estimate of the illuminant is obtained by measuring the maximum of the responses in each channel. The estimation formulation is very similar to that of the GW algorithm in equation (2), except for the fact that *mean* is replaced by the *maximum* of the sensor responses in each channel. It is a subset of the Bayesian approach under the assumption that the reflectance is independent and uniform [49]. The presence of specularities in the images means that the maximum reflectance is greater than pure white and it leads to incorrect illuminant estimation. Alternatively, these specularities can be used to measure the illuminant chromaticity.

2.2.2 Retinex approaches

The Retinex theory introduced in the late 1970's by E. Land [40] is based on the study of image formation in the human eye and its interpretation by the human vision system. This approach investigates color constancy behavior from psychophysical experiments. Land studied the psychological aspects of lightness and color perception of the human vision and proposed a theory to obtain an analogous performance in machine vision systems. Retinex is not only used as a model of the human vision color constancy, but is also used as a platform for digital image enhancement and lightness/color rendition. Land's Retinex theory is based on the design of a surround function [40]. Hurlbert [37] proposed a Gaussian surround function by choosing three different sigma values to achieve good dynamic range compression and color rendition. From that point onwards, numerous Retinex theory implementations were published [7, 14, 27, 31, 39, 41, 46, 48] and effort were made to optimize the performance of the Retinex algorithm by tuning the free parameters [28]. The Multiscale Retinex (MSR) implementation [46] intertwined a number of image processing operations and as a result, the colors are changed in the image in an unpredicted way. Barnard et al. [7] presented a way to make MSR operations more clear and to ensure color fidelity.

2.2.3 Gamut approaches

The concept of gamut approach is based on the work of Forsyth [24] presented in the early 1990's. It can also be referred to as a constraint based approach because color constancy is achieved by imposing constraints on the reflectance and/or the illuminant of the scene. It also imposes hard constraints on the range of occurrence of the illuminant [21, 24]. The implementation of gamut algorithms requires the knowledge of the canonical illuminants. The initial approach was proposed in the *RGB* color space, so it is also referred to as 3D gamut mapping algorithm. It is a two step approach. In the first step, two possible gamuts are obtained namely, the canonical gamut and the image gamut. The canonical gamut is obtained by taking the set of all possible (R, G, B) values due to surface reflectance under canonical illuminant. The choice of the canonical illuminant is arbitrary. Similarly, the image gamut is obtained by taking the set of all possible (R, G, B) values due to surface reflectance under unknown illumination. Both gamuts are convex and are represented by the convex hull. In the second step, under the diagonal assumptions, both convex hulls are mapped. The image gamut is mapped onto the canonical gamut using a linear mapping procedure developed by Forsyth, [24] and called Maloney–Wandell EXTension. MWEXT required both the surface reflectance and illuminants to be selected from a finite dimensional space. This posed some limitation on the MWEXT. Forsyth suggested an algorithm CRULE (based on coefficient rule) to solve for the MWEXT limitations. A heuristic approach was adopted to select a single diagonal mapping from the set of plausible mappings [24]. Finlayson [21] proposed a modification to Forsyth's theory [24] in his work on gamut mapping color constancy in 2D space. Both [21, 24] used the same heuristic approach for the selection of a single mapping matrix. Barnard [9] suggested a mapping selection method based on averaging the set of feasible mappings in both the chromaticity space and the RGB space. This method is based on the assumption that all illuminants and their corresponding mappings are equally probable. Under such assumption, the mean or the expected value is used for the selection of the single mapping. However, in the 2D perspective method [21],unwanted distortion affected the mapping sets; thereby suggesting that the 2D mean estimation for the selection of a single mapping is biased in the chromaticity space. Therefore, Finlayson et al. [20] suggested a mean estimation from the reconstructed 3D maps. Finlayson et al. [19] also proposed angular error and median based mapping selection.

2.2.4 Statistical approaches

Color constancy algorithms discussed under this classification are often based on the basic statistical assumption that the probability distribution of the data is Gaussian. Maximum likelihood is used as the parameter estimator [38]. However, there are some algorithms that applied different probability distributions [49] and parameter estimators [10, 25, 50]. Freeman et al. [25] applied Bayesian theory to color constancy. They provided an insight on how to use all the information about the illuminant that is contained in the sensor response, including the information used by the gray world, subspace and physical realizability algorithms. The algorithms [40, 22] assumed *a priori* knowledge on the illumination distribution. The *a priori* knowledge on the occurrence of the illumination can be assumed to be uniform, i.e., probability of occurrence of all the illuminants is equal. This assumption is fair, if the range of occurrences of the illuminant is not known. Alternatively, if the range of occurrence of the illuminant is known, then *apriori* information on the illuminant can be estimated from a specified set of images within that range.

In their work on Bayesian based color constancy Brainard et al. [10] and Freeman et al. [25] proposed a bilinear modeling technique to estimate the spectral distribution from the statistical information of the illuminants. The prior information was obtained by using principal component analysis (PCA). Skaff et al. [53] extended their work to multiple non-uniform sensors. They developed a multi-sensor Bayesian technique for color constancy by sequentially acquiring measurements from independent sensors. Tsin et al. [56] further improved the work presented in [10, 25] and extended it to outdoor object recognition. They proposed a simple bilinear diagonal color model and an iterative linear update method based on *maximum a posteriori* (MAP) estimation technique. Cubber et al. [15] applied Bayesian framework to achieve color constancy and updated the model in order to achieve correct classification of pixels in their color based visual servoing approach. They assumed a multivariate Gaussian distribution and the dichromatic reflectance model which is limited to inhomogeneous dielectric materials. Rosenberg et al. [49] presented Bayesian color constancy method using non Gaussian models. They replaced the independent and Gaussian distribution of the reflectance with an exchangeable reflectance distribution defined by a Dirichlet-multinomial model. Rosenberg et al. [50] also proposed the Kullback-Leibler (KL) Divergence approach for parameter estimation instead of maximum likelihood approach. Finlayson et al. [18] introduced a new method, known as color by correlation. It is based on the correlation framework to estimate the illuminant chromaticity in the chromaticity space. Barnard et al. [6] extended it to 3D space based on two observations: (i) the pixel brightness makes a significant contribution and (ii) the use of its statistical knowledge is also useful. Sapiro [51] also proposed an algorithm based on the correlation framework for color constancy.

2.2.5 Machine learning approaches

Machine learning algorithms are data based approaches. These algorithms involve two stages, training and testing. In the training stage, the algorithm learns the functional association between the input and the output data. Based on the learning, they predict the output of previously unseen data in the testing stage. So the sample dataset and training algorithms used in the training stage pretty much define these approaches. Therefore, preprocessing of the dataset is very important in order to avoid any undesirable prediction due to outliers(s).

Initial learning approaches to color constancy were based on neural networks. Cardei et al. [13] and Funt et al. [29] in their work on color constancy proposed a multilayer perceptron (MLP) feedforward neural network based approach in the chromaticity spaces. The proposed network architecture consisted of 3600 input nodes, 400 neurons in the first hidden layer, 40 neurons in the second hidden layer and 2 output neurons. They experimented with both synthetic and real dataset. In the case of real images, significantly large numbers of images were required to train the network. Due to the practical limitation of collecting a large number of images, Funt et al. [29] adopted a statistical approach known as *bootstrapping* to generate a large number of training images from a small sample of real images. They showed that neural networks achieved better color constancy than color by correlation [13]. Ebner [17] proposed a neural network performing parallel algorithm in the RGB color space. Moore et al. [44] addressed the issue of multiple illuminations in their application of neural network for color constancy. Nayak et al. [45] proposed a neural network approach in the RGB space to achieve color correction for skin tracking. Stanikunas et al. [54] performed an investigation of color constancy using neural network and compared it to the human vision system. They concluded that background color information is important to achieve human equivalent color constancy in machine vision systems.

Apart from neural networks, there are other machine learning algorithms that have also been applied to achieve illumination invariance description of a surface reflectance. Huang et al. [34] used an adaptive fuzzy based method called fuzzy associated memory (FAM) to recognize color objects in complex background and varying illumination conditions. Funt et al. [26] showed how Vapnik's support vector machines [57] can be applied to estimate the illumination chromaticity and also by incorporating the brightness information. They provided discussion on polynomial and radial basis function kernels. They showed that under controlled (laboratory) conditions support vector machines performs better than neural networks and color by correlation.

3. Problem Statement of Tracking

Video tracking is an active research field in computer vision. The complexity of the research can be understood from the fact that it involves optimal integration between hardware (cameras) and software. Most of modern tracking algorithms require tracking to be performed in real time under unconstrained illumination conditions and in a dynamic environment. These requirements demand that video tracking algorithms be adaptive to factors, such as, color variations, changing background, obstructions, and motion of the target. Therefore, in order to enhance adaptability, tracking algorithms employ multiple moving cameras and take into account a number of features of the target like shape, size, orientation and color. Inclusion of more features enhances the adaptability and robustness of the tracking algorithm, but also adds to the complexity of these algorithms. This is similar to the problem of optimal number of features selection to achieve good classification in pattern recognition. Color is one of the salient features used in tracking algorithms. Therefore, it becomes important to achieve approximate color constancy of the target. If this is achieved in real time, then a number of other factors can be discounted. This signifies the importance of color constancy in real time video tracking applications.

The color constancy algorithms discussed above under each of the individual categories are well established and have been applied under different conditions. From Section 2, we have the conceptual understanding of color constancy algorithms, the circumstances under which they are applicable, and computational constraints. Now, we try to identify, whether it is possible to apply these algorithms in their current form to video tracking.

Sensor based approaches require linear or diagonal transform mapping to obtain illuminant invariant description. These approaches assume that the sensors are calibrated, the spectral response of canonical illumination known, and uniform illumination. They are vulnerable, if these assumptions are violated. In practical applications, these conditions are difficult to achieve, so their application is restricted. Barnard et al. [3] showed that Gray World, Scale by Max, and Gamut mapping algorithms are based on specific assumptions. They also mentioned that most of the algorithms make additional assumptions to achieve solutions. As the assumptions get stronger, the success of the algorithm increases but at the same time its vulnerability to failure also increases if the assumptions fail. Retinex based approaches provide good color rendition and improve the dynamic range of the image, for dark image in particular. However, these algorithms requires parameter optimization to achieve good color rendition. Optimal selection of parameters is not a trivial issue.

Gamut based approaches require mapping between canonical and image gamuts. The selection of single mapping between the gamuts from the plausible mappings is not a trivial issue in both RGB and chromaticity spaces, as discussed in Section 2. These approaches assume knowledge of the canonical illuminants and range of occurrence of the illuminants. These are hard constraint based approaches. Barnard et al. [2] showed that gamut mapping algorithms are the best at achieving color constancy on real images. Funt et al. [30] showed that even gamut mapping is not good enough for object recognition. The non–adaptive nature, dependency on the knowledge of canonical illumination, and computational complexity accounts for the limitation of the gamut approach.

Statistical approaches are widely used in most of the applications. But the assumption about the Gaussian distribution model [38] and prior knowledge of illumination distribution in most cases, restricts its application. Although, researchers have looked beyond those assumptions, they have been applied with limited success in some cases [15]. Color by correlation [18] is a special case of statistical approaches where the distribution was modeled from a fixed set of images. These approaches are adaptive and have been extended to outdoor applications.

Machine learning based approaches provide an interesting alternative to statistical methods. They learn the dependency between the input and the output from the data presented to them and are data driven. Nonlinear machine learning approaches, namely, neural network and support vector machines are applied to estimate the illumination chromaticity and shown to perform better than color by correlation approach as [13, 26]. These approaches are less dependent on assumptions. However, optimization of neural network and support vector machines is a complicated issue due to a number of factors. A discussion on these factors is beyond the scope of this paper, but see [11, 57]. In its present form, both neural networks and support vector machines are less suitable for many practical applications, as they take large training time for a respectable amount of training data. The *advantages* and *disadvantages* of these algorithms are summarized in Table 1.

Color constancy and video tracking are two independent areas of research with individual requirements, constraints, and complexities. From our discussion on color constancy and video tracking in the above sections, we can observe that color constancy is an essential and integral part of video tracking research. The requirement of achieving color invariance under unconstrained tracking conditions, is similar to achieving color constancy in real time. However, it is a challenging problem. In this review, we show that the implementation of most of the current color constancy algorithms is restricted by numerous constraints and assumptions, which are violated in real time tracking.

Statistical based and machine learning-based approaches have shown promise, especially machine learning based approach, which relaxes most of the constraints and assumptions to achieve good color constancy [13, 26]. However, the optimization of parameters of nonlinear learning approaches restricts its application to real time. In our review on machine learning based approaches for color constancy, we observed that linear machine learning algorithms have not been tested for color constancy. It is an unexplored field of research in color constancy. If linear learning techniques can model the association between the color in the image and illumination chromaticity, then there is a potential that color constancy can be achieved in real time video tracking.

4. Conclusions

The main purpose of this review was to evaluate current color constancy algorithms based on their algorithmic approaches, highlight the importance of color constancy in real time video tracking, and identify whether the reviewed algorithms can be applied to video tracking in their present form. On the basis of our review and comparison of different color constancy approaches, we observed that the application of the reviewed approaches to real time video tracking has been limited. All the algorithms reviewed in this paper make some assumption about the statistics of the reflectance to be encountered, and most make assumptions about the illuminants that will be encountered. The gray world algorithm makes assumptions about the expected value of scene average, scale by max algorithm makes the assumptions about the maximum value in each channel and the gamut mapping algorithms make assumptions about the ranges of expected reflectances and illuminants. Besides these specific assumptions, each of the algorithms makes additional assumptions of flat surface and homogeneous illumination conditions. Moreover, most machine color constancy approaches cannot handle situations with more than one illumination present in the scene.

The dependency of color constancy algorithms on assumptions has restricted its application to unconstrained practical applications like video tracking. Furthermore, their comp-

Table 1: Advantages and disadvantages of color constancy algorithms.

Classification methods	Advantages	Disadvantages
Pre-Calibrated approaches	– Performs good color constancy if sensor characteristics are known.	– Requires sensor pre-calibration.
Gray World and Scale by Max approaches	– Computationally less expensive. – Analytical solution is possible.	– Less reliable and not adaptive. – Depend higly on assumptions.
Retinex approaches	– Improves the visual appearance of images. – Performs better on dark images.	– Poor color fidelity. – Requires optimal selection of free parameters.
Gamut approaches	– Better color reproduction than other approaches.	– Computationally expensive. – Depends upon sensor sensitivity. – Assumes uniform illumination distribution. – Requires knowledge of the range of illuminant.
Statistical approaches	– Adaptive to changing illumination conditions. – The illumination distribution is obtained from the knowledge of statistical probabilistic distribution. – Prior knowledge of the illumination is not mandatory.	– In real time applications statistical assumptions are violated. – Computationally expensive in terms of time.
Machine learning approaches	– Adaptive to changing illumination conditions. – Color constancy can be achieved from approximate knowledge of illumination chromaticity.	– Algorithms discussed are unstable and require large training time. – It is difficult to regularize the estimation of illumination chromaticity.

utational compelxity does usually not allow for real time computations without using additional special hardware. One way to overcome these restrictions in the future can be to design tracking algorithms that are less sensitive to color constancy and at the same time to achieve rough estimations of color constancy with fewer assumptions, in less time. For example, machine learning approaches showed less dependency on assumptions, but their implementation requires optimal selection of number of parameters which imposes restriction on their application to video tracking. Machine learning based approaches, like ridge regression and kernel regression have not been evaluated to estimate illumination chromaticity. It will be interesting in the future to evaluate the performance of either of these approaches in achieving color constancy. The performance of these algorithms will be of interest from the real time color constancy point of view in video tracking.

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