Improving Assistive Software for Color Vision Deficiency through Multiple Model Aggregation

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Abstract
Assistive software that recolors images for individuals with color vision deficiency relies on models of the color differentiation abilities of its intended users. Situation-specific models address the shortcomings of current assumption-based models by using in-situ calibration to capture the color differentiation abilities of a specific user in a specific environment. However, this calibration procedure is time consuming, and when the user is unable to perform it, the assistive software fails to recolor properly. To address this problem, we propose a collection of situation-specific models—Multiple Model Aggregation (MMA)—that can be used to instantly provide the best previously-generated model to the assistive software with no input required from the user. Design challenges for extending MMA to any model-based system are also presented.

Keywords
Model aggregation, color vision deficiency

ACM Classification Keywords
H.1.2 User/Machine Systems, H.5.m miscellaneous.

General Terms
Design, Human Factors, Performance

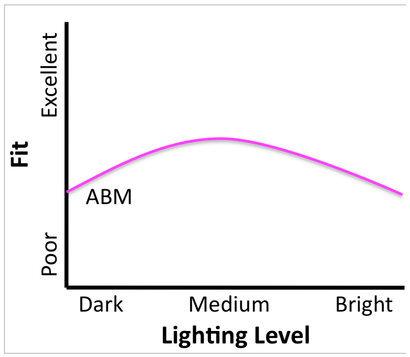

Figure 1. A hypothetical assumption-based model that fits well at medium light levels, but fits less well at dark and bright light levels.

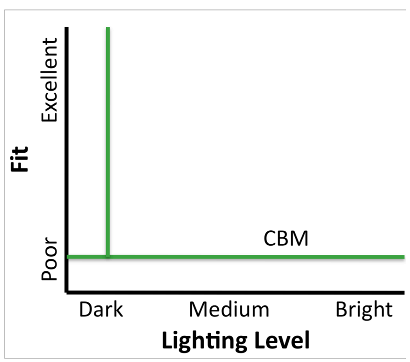

Figure 2. A hypothetical situation-specific model that that was generated in a dark environment fits very well at dark light levels, but poorly elsewhere.

Introduction

Individuals with color vision deficiency (CVD) confuse colors that the rest of the population do not confuse. To help overcome the problems arising from this confusion, color adaptation software has been developed that modifies the colors presented on a display to make them more differentiable for the user with CVD [4,5,7]. This adaptation software relies on models of the color differentiation abilities of the user.

The common approach to modeling these color differentiation abilities is to make assumptions about properties of the user and the environment to construct a model that is applicable to the most common situations (assumption-based model) [2,6]. Examples of properties for which assumptions are made are the type of CVD the user has, the lighting level, and the color adjustment of the display. Assistive software that relies on this model will be useful in situations that meet the assumptions, but will be less useful in situations that do not satisfy them (Fig. 1).

Situation-specific models address the shortcomings of assumption-based models by using an in-situ calibration to capture the color differentiation abilities of a specific user in a specific environment [1,3,8]. This allows a situation-specific model to accurately represent the color differentiation abilities of any user in any environment, assuming that the user is willing to perform the calibration in that environment (Fig. 2). However, this calibration procedure is time consuming (around 30 minutes), and needs to be performed whenever the situation changes. When the assistive software requires a new situation-specific model, but the user is unable or unwilling to perform the calibration, the assistive software becomes less useful.

Assumption-based models are not sensitive to variations in the user or the environment that violate the assumptions used to build the model. Situation-specific models are not able to be calibrated quickly enough to be useful in every situation. No current modeling approach can quickly provide situation-specific models to assistive software for individuals with CVD.

To address this problem, we propose a collection of situation-specific models—Multiple Model Aggregation (MMA)—that instantly provides the best previously-generated model to the assistive software with no input required from the user. This is accomplished by arranging the collection of models according to the properties of the user and the environment for which each model was constructed. When a new model is needed, the MMA system searches for a model that matches the new properties. This model is then returned to the assistive device to immediately provide assistance that is sensitive to the current situation.

In this paper, we present an algorithm and design considerations of the MMA approach. We then explore four key challenges to extending any model-based system to MMA.

Multiple Model Aggregation

In this section, we will present a basic algorithm of how the MMA system operates. This will be followed by a discussion of MMA design and implementation considerations.

Algorithm

1. determine that a new model is needed
2. send user and environment properties to MMA

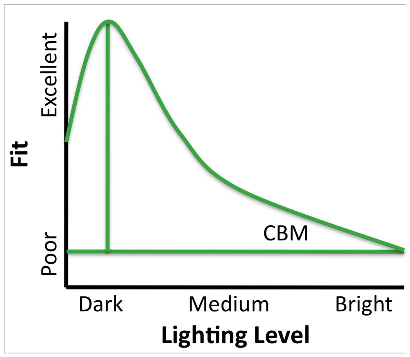

Figure 3. Extending Fig. 2 to other light levels. Model fitness decreases as the light level diverges from original calibration light level.

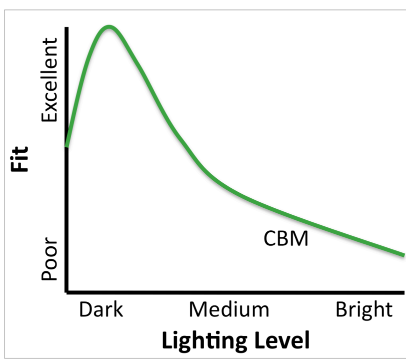

Figure 4. The extended curve from Fig. 3 represents the true model fitness of the situation-specific model presented in Fig. 2.

3. MMA searches for an appropriate match
4. if not a perfect match, then extrapolate to fit search properties
5. return the model to the assistive software
6. assistive software switches to this new model

Design Considerations

WHEN TO REQUEST A NEW MODEL? (ALGORITHM STEP 1)

There are three options for stimulating the choice to request a new model: user driven, assistive software driven, and MMA driven. With the user stimulating the choice, they must be able to discern that their ability to differentiate colors is decreasing (which may not always happen). It may be a better option to allow the decision to be made automatically, either by the assistive system or the MMA system. If the assistive system is to make the decision, then it can monitor the relevant properties of the user and the environment (preferably via non-intrusive techniques, such as sensors). When the change in a property exceeds a threshold, then the assistive system can send the new property information to the MMA system in order to obtain a new model. If the MMA system is responsible for determining when new models should be provided, then the assistive system can periodically report the user and environment properties. When a property exceeds some threshold, the MMA system can provide a replacement model that matches the new properties.

HOW TO EXTRAPOLATE AN EXISTING MODEL TO FIT NEW PROPERTIES? (ALGORITHM STEP 4)

This is still an open research question. Situation-specific models are calibrated by a particular user in a particular environment, and it is unknown how they generalize to other situations without recalibration. Flatla and Gutwin [3] did evaluate their situation-specific model using varying factors (lighting level, background, monitor settings, and fatigue), and found that their model was robust to small changes in these factors. It is on this early evidence that the generalization presented in Figs. 3 & 4 is based.

USER INPUT FOR MODEL SWITCHING (ALGORITHM STEP 6)

When the assistive software switches to a new model, the colors presented on the display may abruptly change. When the user has just entered a dramatically new environment (e.g., moving from a dark hall to bright sunshine), they may welcome the abrupt transition as a sign that the system is recognizing the transition. Alternatively, colors frequently changing when it does not seem necessary to the user (e.g., whenever someone walks by casting a diffuse shadow on their desktop display), will frustrate the user. The user should be given the option to allow a new model to be used (but frequently pestering the user can be irritating as well).

Challenges for General Extension

The MMA approach presented in this paper can be extended beyond assistive software for individuals with CVD to any model-based system that can facilitate situation-sensitive modeling. We now explore a number of general challenges to moving systems to MMA.

Parameters for Searching in MMA

In order to find a model in the collection, the collection must be searchable. Each model represents some data that has been collected under a very specific situation. Properties of this situation can be used to search the collection. Some properties will be more valuable than others for identifying the best possible model. It needs to be determined which properties (e.g., user, system,

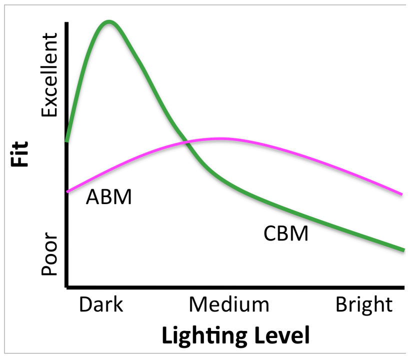

Figure 5. Overlapping the fitness of the assumption-based model in Fig. 1 with the fitness of the situation-specific model extension in Fig. 4.

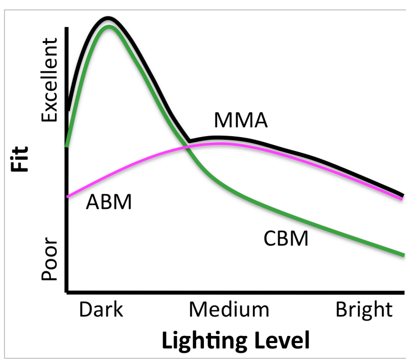

Figure 6. With Multiple Model Aggregation, a new modeling approach that attains maximum fit is available.

or environment) are the most valuable for finding the model that best matches the current situation. The collection of properties presents an implementation challenge to be resolved, since they can be collected from the user, from sensors, or from user or machine profiles.

Increasing Coverage for Each Model
Current approaches to situation-specific modeling produce models for a very specific situation. These models represent a tiny point in the (often large) parameter space of these models. It remains to be determined how the generalization of situation-specific models without recalibration can be performed.

Reasonable Default Model
If there is insufficient models in the collection, some reasonable default is necessary so a model can always be delivered by the MMA system when requested. If a general assumption-based model exists (as it does for CVD), then this can be used as a reasonable default model. The use of an assumption-based model as a default is illustrated in Figs. 5 & 6.

Increase Number of Models
To maximize the value of MMA, any and all situation-specific models must be recorded for future use. To facilitate this, a community-based MMA can be developed. In this approach, *every* model generated would be added to one large global collection, from which models are drawn. This may require that the search parameters of the MMA are reconsidered, as comparisons between individual will need to be made to find similarities. This would also involve other considerations of community, such as trust, ratings, and reputation.

Conclusion
In this paper, we proposed multiple model aggregation to overcome the problems resulting from lengthy calibration times inherent in situation-specific models. This approach provides highly specific models to CVD assistive software systems with no time penalty, and can be extended beyond CVD assistive systems to general model-based systems.

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