Genetic Algorithm Automated Generation of Multivariate Color Tables for Visualization of Multimodal Medical Data Sets

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Abstract

In many applications there is a need to visualize multidimensional data sets. Using spatial relationships alone, display is limited to two or three dimensions. The use of color, in addition to spatial relationships, increases the dimensionality of the data that can be effectively visualized. Use of color is usually achieved through the application of color tables. The generation of color tables is not an easy task, and since color space is relatively large it is nearly impossible for an individual to consider all of the possible options. A genetic algorithm was developed to automate this task, generating color tables for the joint display of high-resolution and dynamic contrast-enhanced magnetic resonance imaging and F-18-FDG positron emission tomography data sets. The results are promising, producing new color tables that meet defined requirements.

1. Introduction

In this paper the use of two dimensional color tables for the fusion of medical images is explored. After a discussion of the task at hand, and the considerations that need to be made, desirable properties of the color tables are defined. A genetic algorithm for automatic generation of color tables that have the desired properties is proposed. The advantage the proposed method has over other color table generation techniques is its ability to consider a much larger set of possible color tables, ensuring that the optimum color table for a given application is found. The paper concludes by showing samples of multimodal medical images created using the generated color tables.

1.1. Color Table Selection is Task, Observer, and Environment Dependent

One very important fact that needs to be kept in mind when selecting which color table to use is that the choice should be both application and observer dependent. It is also necessary to consider environmental factors that affect how observers will perceive the displayed colors.

It is well known that various vision deficiencies, such as deuteranomaly, influence how individuals perceive color. This means that in general there will not be a color table that is ideal for everyone. Even among those without any documented vision deficiencies, the choice of the optimal color table will vary with factors such as experience and training.

The viewing conditions also play a role in selecting the most appropriate color table. This includes conditions such as the lighting in the room, the color of the background, and the gamma and black offset of the display device.

When generating color tables using the genetic algorithm described in this paper these factors are ignored. It is assumed that gamma corrections as well as other corrections for viewing conditions will be applied to the color table prior to deploying it into the environment. The color tables generated are intended for a general audience, and are not tuned towards any one individual. This has to be so if the color tables are to be deployed in a clinical setting.

It is a necessity however, to consider the task that the images produced by the application of the color table are going to be used for. See [1] for a full demonstration of how a properly designed color table can aid a task while an improperly designed one can complicate matters. Because of this, it is first necessary to define the task at hand and then the requirements of the color tables that will aid in this task.

1.2. The Task - Multimodality Breast Cancer Imaging

Application of a multimodality approach is advantageous for detection, diagnosis and management of breast cancer. In this context, F-18-FDG positron emission tomography (PET) [2, 3], and high-resolution and dynamic contrast-enhanced magnetic resonance imaging (MRI) [4, 5] have steadily gained acceptance in addition to x-ray mammography and ultrasonography. Initial experience with combined PET (functional imaging) and x-ray computed tomography (CT, anatomical localization) has demonstrated sizable improvements in diagnostic accuracy, allowing better differentiation between normal and pathological uptake and by providing positive finding in CT images for lesions with low metabolic activity [3].

Obtaining the spatial relationships between these modalities and conveying them to the observer maximizes the benefit that can be achieved. The process of obtaining the spatial relationships and manipulating the images so that corresponding pixels in them represent the same physical location is called registration.

A method has been developed for the 3D non-rigid coregistration of PET and MRI images [6, 7]. Coregistration of PET and MRI images provide additional information on morphology (including borders, edema, and vascularization) and on dynamic behavior (including fast wash-in, positive enhancement intensity, and fast wash-out) of the suspicious lesion and allows more accurate lesion localization including mapping of hyper- and hypo-metabolic regions as well as better lesion-boundary definition. Such information might be of great value for grading breast cancer and assessing the need for biopsy. If biopsy is needed, it could be precisely guided to the most metabolically active (i.e. most malignant) region.

The next step is the visualization of the data. Traditionally the registered images are displayed side by side. However, it is believed that a combined MRI/PET display may be more beneficial. The advantage of a combined image lies in our inability to visually judge spatial relationships between images when they are viewed side by side. Depending on background shades and colors, identical shapes and lines may appear to be different sizes [8]. The fact that the spatial relationships between the modalities can better be ascertained from a combined display drives this research.

The process of combining the MRI and PET images into a single image is called fusion. The color tables generated and studied in this work are to be used to create fused MRI/PET images.

1.3. Fusion Techniques for Visualization

There has been much research devoted to discover new and optimum ways to take two images and display them as a single one. These techniques include color overlay, color mixing, techniques based directly on color spaces, and spatial and temporal interlacing. For a review of these techniques see [9]. Usually these techniques are applied to the data and the results are compared in order to determine the best visualization technique.

An interesting fact is that a two dimensional color table can be used to implement all of these techniques with the exception of interlacing. This facilitates an alternative approach to discovering the best visualization technique. Trying out each visualization technique and determining optimum parameters is time consuming, instead this paper proposes to focus on finding the best two-dimensional color table.

This is not a new approach and a lot of effort has been expended on studying the design of color tables, how various properties of them affect the perception of the displayed images, the role the images that the color table is being applied to play, and on techniques to compare the color tables [1, 10, 11].

1.4. Two Dimensional Color Table Basics

Color tables, also known as color maps, are a simple yet powerful tool. The grayscale values of the two source images for a given pixel serve as indices in the color table. Looking up the indices in the color table gives the color that the same pixel in the fused image should have.

For an example see Fig. 1 of a 3x3 color table. The vertical numbering represents intensity values in the first source image, while the horizontal numbers represent intensity values in the second source image. If the first source image is given by Fig. 2 and the second source by Fig. 3, then using this color table to fuse the two images will result in Fig. 4.

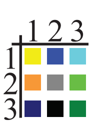

Figure 1

1	3
2	2

Figure 2

2	3
1	3

Figure 3

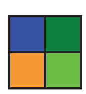

Figure 4

1.5. Drawbacks of the Color Table Approach

Color tables are often created by hand, and are usually evaluated by humans. The biggest drawbacks of this approach are that the color tables tend to be large, and that it is only feasible to evaluate a small number of them.

The size of the color table depends on the number of discrete values in the sources to be displayed, and the number of colors the display device has access to. For example if there are two 8-bit sources, there will be 256*256 entries in the color table. Assuming an 8-bit display, each entry can be one of 256*256*256 colors. Considering every color for each entry is a nearly impossible task for a human. This problem is usually avoided by selecting and using one of the previously mentioned fusion-for-visualization techniques. The problem with taking one of these approaches is that only a small set of the possible color tables are considered. In this paper a new genetic algorithm based color table creation method is introduced. In theory, this method will search through the space containing all possible color tables in order to produce one that best represents a set of criteria.

Evaluation of the color tables is usually done directly by humans, and unless vast human resources exist only a small number of color tables are considered for a particular task. In this paper a simple technique for automatic evaluation of color tables will be presented. While this technique is not meant to replace human evaluation, it can be used to pre-evaluate a large set of color tables, guiding the genetic algorithm in selecting color tables for human review.

2. Extension of Color Mixing

Color mixing is a technique discussed in [9] that can be used to take any number of one channel images (N) and create a fused RGB image. It is performed using Eq. 1. Here R, G, B represent the red, green, and blue channels in the displayed image respectively, S_i represents the intensity in the i^{th} source image, R_i, G_i, B_i are the weighting factors for the red channel, green channel, and blue channel. They determine the contribution of source i to each of the output channels.

$$\begin{pmatrix} S_1 & S_2 & \dots & S_N \end{pmatrix} \begin{pmatrix} R_1 & G_1 & B_1 \\ R_2 & G_2 & B_2 \\ . & . & . \\ . & . & . \\ . & . & . \\ R_N & G_N & B_N \end{pmatrix} = \begin{pmatrix} R & G & B \end{pmatrix} \tag{1}$$

Let the source intensities be normalized from zero to one. Applying Eq. 1 is then equivalent to taking the intensity axis of source i and lying it along the line segment formed by connecting (0,0,0) to (R_i, G_i, B_i) in the RGB color space. The output image is then formed by summing the projections of each of these onto the red, green, and blue axes.

The technique can be extended by allowing the vectors (R_i, G_i, B_i) to point in any direction. So for example as the source intensity increases the red in the fused image decreases. The technique can also be extended by using an offset so that the vectors, (R_i, G_i, B_i), do not need to be located at the origin. After making these extensions the color mixing technique can be represented by Eq. 2. Where O_{Xi} represents the offset from the origin along the X axis for the contribution from source i.

$$(R,G,B)=\left(\sum_{i=1}^{N}(S_iR_i+O_{Ri}),\sum_{i=1}^{N}(S_iG_i+O_{Gi}),\sum_{i=1}^{N}(S_iB_i+O_{Bi})\right) \tag{2}$$

3. Generating the Color Tables

3.1. Color Table Requirements

Before an algorithm which generates color tables can be created, there needs to be a way to quantitatively define guidelines or requirements to be used when generating the color tables. The result of evaluating a color table with these guidelines will be the fitness factor used to determine the reproduction of the color tables within the genetic algorithm.

To aid in defining these guidelines a way to determine the difference between two colors is first introduced. Traditionally this difference is defined as the Euclidean distance between the two colors in the CIE L*a*b* space and is given by:

$$\Delta E=\sqrt{(\Delta L^*)^2+(\Delta a^*)^2+(\Delta b^*)^2} \tag{3}$$

The validity of this Eq. 3 comes from the assumption that the CIE L*a*b* color space is uniform. It has been shown that this assumption is not quite true [12]. For this reason, and to enable a more efficient implementation, we choose to use the more recently developed computationally efficient measurement used by CompuPhase in their PaletteMaker application [13].

$$\begin{aligned}
\bar{r}&=\frac{C_{1,R}-C_{2,R}}{2}\\
\Delta R&=C_{1,R}-C_{2,R}\\
\Delta G&=C_{1,G}-C_{2,G}\\
\Delta B&=C_{1,B}-C_{2,B}\\
\Delta C&=\sqrt{(2+\frac{\bar{r}}{256})*(\Delta R)^2+4*(\Delta G)^2+(2+\frac{255-\bar{r}}{256})*(\Delta B)^2}
\end{aligned} \tag{4}$$

Here ΔC is the difference between the two colors defined in RGB space as $(C_{1,R},C_{1,G},C_{1,B})$ and $(C_{2,R},C_{2,G},C_{2,B})$, where $C_{X,Y}$ is the value for the Y^{th} channel for the X^{th} color, and has values from 0 to 255. For further discussion of this metric see [14].

This definition of color difference aided in defining the requirements for the color tables which follows.

3.1.1. Resulting Color Table should be in the RGB Color Space

It was decided that the color tables produced need to be defined in the 8-bit per channel RGB color space supported by most applications. This is required in order to facilitate easy use and guaranteed compatibility of the color tables produced. This was taken into consideration when selecting the formula for color differences.

3.1.2. Resulting Color Table should satisfy the Order Principle

In [15] Trumbo defines several desirable properties of color tables. One of these is the order principle. If a color table satisfies the order principle, then the colors chosen to represent the data values should be perceived as ordered in the same order as the data values. This rules out spectral color tables where large variations of hue occur. This is important because the pixel values in the original medical data represent physical quantities, such as the concentration of F-18 decay in the PET images. This is the information radiologists need to have, if one pixel is shown as blue and another red, the radiologists will be unable to determine which pixel has a higher concentration without referring to the color table. While the color table will not be a secret from the radiologist evaluating the fused data, the less they need to refer to the color table the more efficiently they can examine the data.

Also, a side effect of a color table not satisfying the order principle is that the color table often creates false segmentation when applied to the image. The color contours created in the image emphasize particular pixel values.

To guarantee that the order principle is satisfied, a representation of the color table based on the color mixing technique introduced in [9] and previously discussed here is used by the algorithm. The linearity imposed by the color mixing model ensures that the order principle will be satisfied. The use of the color mixing technique limits the set of possible color tables the genetic algorithm can evaluate, but greatly simplifies the quantitative definitions of the color table requirements.

3.1.3. Resulting Color Table should satisfy the Rows and Columns Principle

The rows and columns principle is also defined by Trumbo in [15]. It states that the colors in the color table should be chosen so that the two source images do not obscure one another.

This is particularly important in this situation. Each of the input images and their gray levels mean something to the radiologist. This meaning needs to be preserved in the fused images. The radiologist needs be able to tell the intensity of each of the source images by examining the fused image.

This is partially ensured by making the one dimensional color tables corresponding to each source as different as possible from each other. In other words the first row of the color table should consist of colors as different as possible from the first column. This can quantitatively be measured by maximizing ΔC, in Eq. 4, for the average color in the first row of the table and the average color for the first column in the table. Due to the linear model of the color mixing technique this property will then be distributed throughout the rest of the color table.

By making the color used for each source as different as possible we prevent the obscuring of the sources that would occur if they used similar colors. Opponent color theory suggests that other color combinations can result in obscuration of the sources. We do not at this time however, consider the implications of opponent-color theory.

3.1.4. Resulting Color Table should be Perceivably Uniform

The ideal color table should be perceivably uniform. In other words the ΔC between neighboring entries in the color table should be a constant throughout the table. This can be measured by finding ΔC for all neighbors and then examining its variance. A smaller variance means a more uniform color table.

This is an important factor because it minimizes the reliance on the color table, due to the fact that the radiologist's intuition about the location of the color in the color table is more likely to be correct.

3.1.5. The Contrast for Each Source should be Maximized

The contribution from each source should have as much contrast as possible. As contrast increases for a source it gets easier to see the variations in the fused image due to that source. Due to using the color mixing model we need only to examine the endpoints of the first row and column of the color table to know the range of colors available for each of the sources to use.

Maximizing ΔC between the first entry in the first column and the last entry in the first column of the color table will maximize the contrast for the first source. Similarly, maximizing ΔC between the first entry in the first row and the last entry in the first row of the color table will maximize the contrast for the second source.

As a final measure to ensure good contrast throughout the color table it is desirable to have the contrast along the diagonal of the color table maximized. This is done by maximizing ΔC for the first entry in the first row and column of the color table and the last entry in the last row and column of the color table.

3.2. Desirable Properties Not Considered

It should be noted that in the current implementation the algorithm does not consider all of the desired properties of a color table. For example, no preference is given to any particular color. Humans may find some colors easier to look at and examine for long periods of time than others.

Simultaneous contrast and chromatic contrast effects as described in [10] are not considered. These effects describe how the appearance of a particular color may change based on the surrounding colors in the image.

Another effect that the human visual system has on images that is usually ignored is that the color of an object influences its perceived size [16, 17]. For example, if we color a lesion red-purple it would appear larger than if it had been colored green.

3.3. Genetic Algorithm for Generating Color Tables

A relatively simple and standard genetic algorithm is used for the generation of the color tables. Each color table is defined by 12 real numbers that have a range from -1 to 1. These numbers represent the following variables from Eq. 2: R_1, O_{R1}, G_1, O_{G1}, B_1, O_{B1}, R_2, O_{R2}, G_2, O_{R2}, B_2, O_{B2}. These coefficients when used with the color mixing equation completely define a color table.

To start an initial population of color tables is randomly generated. An iterative loop is then entered. Each member of the population is then evaluated and ranked based on the requirements of the desired color table. A new population is then generated, where the contribution from each member of the previous generation to the new generation is based upon its ranking. This process is repeated for a large number of iterations.

To evaluate a population of color tables they are tested for each requirement as previously described. The numeric results of the evaluation of a given color table can then be weighted and summed to give the fitness score for that member of the population.

The members of the current generation with the highest fitness scores are automatically included in the next generation. The rest of the members in the next generation are created by splicing or mutating the members in the current population.

When creating a population member by mutation, a member of the previous generation is chosen randomly with a probability proportional to its fitness score. The new population member is then created from the old one by making one or two random changes to its defining coefficients.

When creating a population member by splicing, two members of the previous generation are chosen at random with a probability proportional to their fitness scores. The new population member is generated by taking the first X coefficients of it from the first chosen member and remaining 12-X coefficients from the second member. The point of splicing, X, which determines the amount of each of the chosen color tables that gets transferred to the new color table, is chosen at random.

For the stopping criteria the algorithm can be halted when the member with the highest fitness score does not change for a number of generations. There is no fear of running the algorithm for too many generations due to the nature of the problem.

After the algorithm has finished executing, the member of the final population with the highest fitness score represents the 'best' color table that the algorithm could come up with. The algorithm can be run several times to get a set of color tables that can then be evaluated by human observers.

5. Conclusions and Future Work

The algorithm was used to successfully generate a number of color tables that met the defined requirements. Figs. 5-6 show a couple of these color tables. Fused images created using these color tables are shown in Figs. 8-9 respectively. The original MRI image is Fig. 11 and the original PET image is Fig. 12. The fused images were created using the KGB Fusion Viewer software package [18]. For comparison the fused image that would result from using the Mayo Clinic's popular Analyze software package [19] is shown in Fig. 10. The corresponding color table is shown in Fig. 7.

It is believed that an improvement in diagnostic accuracy can be achieved using the newly generated color tables. A study comparing the usefulness of the fused images created using the color tables generated by this algorithm with the images created using other popular fusion techniques is underway. The radiologists from University Hospital in Syracuse are participating in this study.

There are several areas where the algorithm can be improved. Besides considering the other desirable properties discussed in section 3.2 of this paper, the test for compliance of the rows and columns principle should consider the implications of opponent color theory. Furthermore the algorithm should be expanded to consider the set of all 2D color tables instead of just those that can be represented using the extended color mixing model. The most complex part of this expansion will be the redefinition of the tests for the desired properties of the color tables.

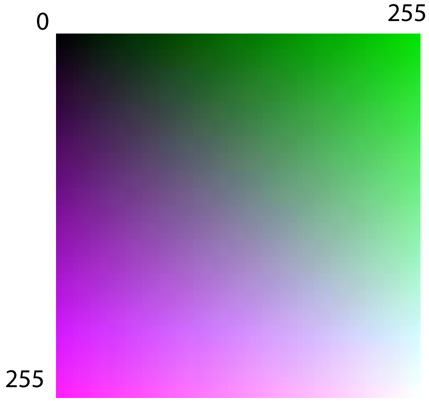

Figure 5. *Sample color table generated using genetic algorithm.*

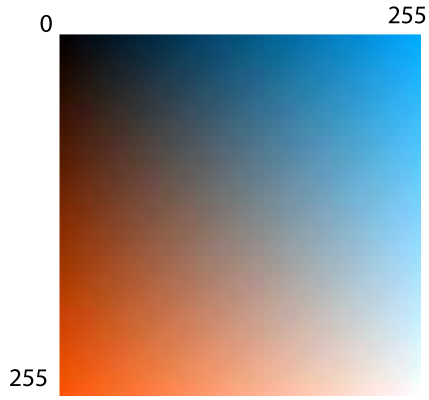

Figure 6. *Sample color table generated using genetic algorithm.*

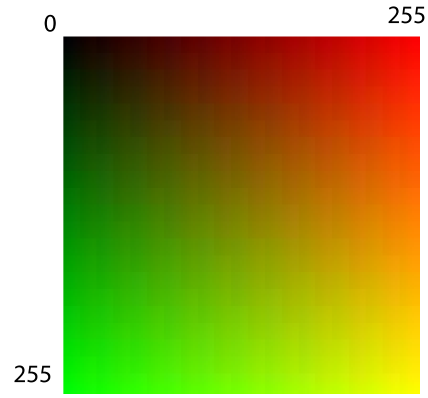

Figure 7. *Sample color table corresponding to the red/green fusion provided by Analyze.*

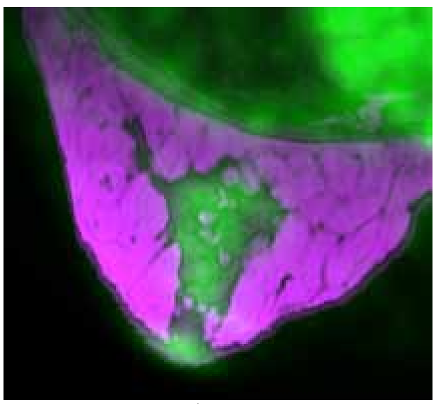

Figure 8. *Fused MRI/PET image created using the color table shown in Fig. 5. Source images are shown in Fig. 11 and Fig. 12.*

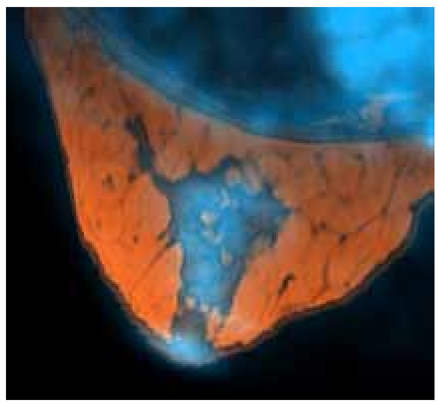

Figure 9. *Fused MRI/PET image created using the color table shown in Fig. 6. Source images are shown in Fig. 11 and Fig. 12.*

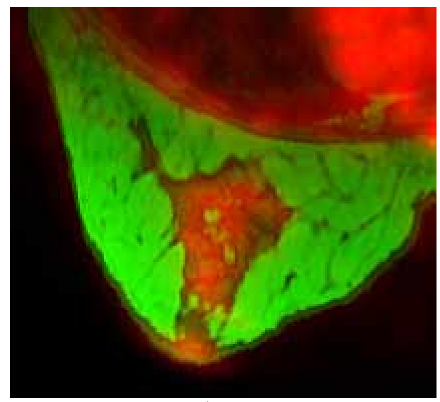

Figure 10. *Fused MRI/PET image created using Analyze. Source images are shown in Fig. 11 and Fig. 12.*

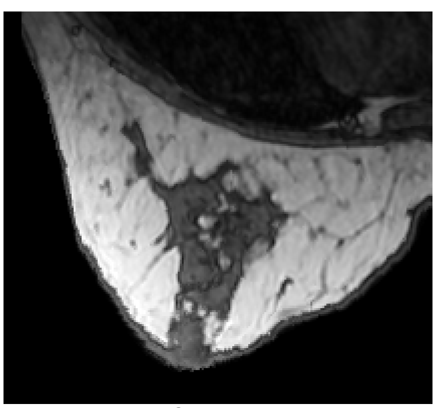

Fig. 11. *Original MRI Image.*

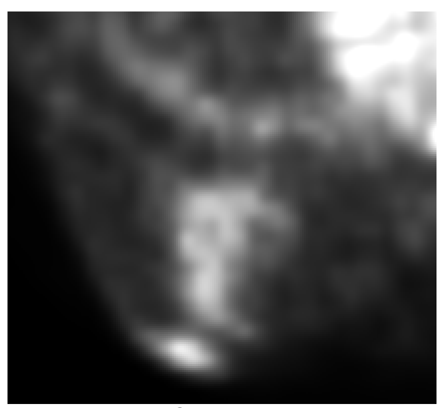

Fig. 12. *Original PET Image.*

6. References

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