Using False Colors to Protect Visual Privacy of Sensitive Content

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ABSTRACT

Many privacy protection tools have been proposed for preserving privacy. Tools for protection of visual privacy available today lack either all or some of the important properties that are expected from such tools. Therefore, in this paper, we propose a simple yet effective method for privacy protection based on false color visualization, which maps color palette of an image into a different color palette, possibly after a compressive point transformation of the original pixel data, distorting the details of the original image. This method does not require any prior face detection or other sensitive regions detection and, hence, unlike typical privacy protection methods, it is less sensitive to inaccurate computer vision algorithms. It is also secure as the look-up tables can be encrypted, reversible as table look-ups can be inverted, flexible as it is independent of format or encoding, adjustable as the final result can be computed by interpolating the false color image with the original using different degrees of interpolation, less distracting as it does not create visually unpleasant artifacts, and selective as it preserves better semantic structure of the input. Four different color scales and four different compression functions, one which the proposed method relies, are evaluated via objective (three face recognition algorithms) and subjective (50 human subjects in an online-based study) assessments using faces from FERET public dataset. The evaluations demonstrate that DEF and RBS color scales lead to the strongest privacy protection, while compression functions add little to the strength of privacy protection. Statistical analysis also shows that recognition algorithms and human subjects perceive the proposed protection similarly.

Keywords: Visual privacy protection, false color visualization, objective evaluation, subjective assessment.

1. INTRODUCTION

The advances in imaging technologies, widespread use of social networks, and rapid adoption of surveillance systems have created a situation where we are under the constant surveillance with daily violation of personal privacy. While social networks, photo and video sharing platforms, and cloud based services provide privacy and security protection mechanisms (albeit being rudimentary and inefficient as recent privacy scandals demonstrated), little is done for privacy protection in video surveillance systems.

One reason for the lack of use of privacy protection tools in video surveillance is the problem of balancing between privacy, the amount of personal information visible in a video, and intelligibility, the amount of visible information that is necessary to perform a surveillance task. An ideal video surveillance system should protect privacy without sacrificing intelligibility. This means, for instance, that unauthorized individuals should not be able to recognize people in a protected surveillance video but, if need be, authorities such as police, should be able to access the full content of the video during a potential criminal investigation. Furthermore, it should be possible to infer information from the protected video that is useful for the surveillance application without revealing the identities of the people. For example, determining the crowd density in a given region, the direction in which a group of people is moving, or the actions performed by people should be possible without revealing the identities of each individual involved in these scenarios.

Although many methods for privacy protection exist, most of them rely on computer vision algorithms, such as face or person detection, for identifying the privacy sensitive regions where the protection should be applied to. However, computer vision algorithms are not always accurate and may fail in certain cases such as poor capture conditions, noise in the captured

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frames, partial occlusion of the individuals, and non-ideal camera viewpoints or field-of-views. The failure even in a single frame of a video can lead to the loss of the privacy protection efforts. Therefore, a method that is independent on the underlying computer vision algorithms is needed for more robust privacy protection.

This paper proposes a computer vision independent method that utilizes simple intensity compression/expansion schemes and false color visualizations. To this end, the intensity values of a face image are first compressed and then transformed to a different color scale. For compression, three different functions are used, including logarithmic, sigmoidal, and histogram equalization. An uncompressed condition is also used to evaluate the effectiveness of only using false colors. For false coloring, four different palettes are tested, namely the rainbow, Radiance default*, heated-body, and the linearized optimal color scales. The objective (based on the evaluation framework proposed in[2]) and crowd-based subjective (based on the approach by Rogowitz and Kalvin[3]) experiments, were conducted using 100 images of the public FERET face dataset[4] and show that the proposed approach can effectively protect privacy of faces. Furthermore, the proposed scheme is reversible in a way that all operations can be reverted to obtain the original images. Finally, the protected images retain most of the information necessary for the surveillance task without revealing personal identifiable details.

Therefore, the following are the main contributions of the paper:

- Privacy protection method based on false color scale and intensity compression is proposed. Because the method preserves the semantic structure of an image, it can be applied to the whole image without the need of identifying privacy sensitive regions using typically inaccurate computer vision algorithms.
- Both objective and subjective evaluations of the method are performed, and their results are compared. Four color scales and four compression schemes are evaluated.
- The detailed analysis is performed to determine which scale is the most suitable for privacy protection in cases when both machines and humans are the observers.

2. BACKGROUND AND RELATED WORK

A large number of privacy protection methods are proposed in the literature which can be classified into two major groups. The first group of algorithms determine a region of interest (ROI) from the input frame and applies privacy protection only in this region. In the second group, privacy protection is performed on the entire frame. In the remainder of the paper we refer to these two groups as *local* and *global* methods respectively. Most of the existing privacy protection methods fall into the local category. The chief drawback of local methods is their reliance on computer vision techniques. That is, if the sensitive regions are not correctly identified, the privacy of the recorded individuals may be compromised.

Privacy protection algorithms can be classified along other dimensions as well. For example, some privacy methods are format/compression dependent while others are format/compression independent. The former methods only work for certain image or video formats such as JPEG or MPEG. Format independent methods do not place any restriction on the format of the content that they process. Privacy protection methods can also be classified based on their reversibility. Reversible methods enable the original image or video to be recovered from the protected versions assuming that a secret key is known. Irreversible methods, on the other hand, do not provide a mechanism to obtain the originals.

The three simplest methods of privacy protection are masking, blurring, and pixelation. Masking corresponds to painting the sensitive regions with an opaque color (e.g., insertion of a black box). Although this maximizes privacy, it is not only irreversible but it may also prevent acquiring non-sensitive information as well. Blurring involves smoothing the sensitive regions with a blur kernel. Using a large kernel radius may enhance privacy protection but it may also hinder reversibility. Using small kernels, on the other hand, may not ensure sufficient privacy. Pixelation methods transform the selected regions into a mosaic-like pattern effectively reducing the resolution of the sensitive regions. Their advantages and disadvantages are similar to that of blurring.

More advanced privacy protection methods have also been proposed such as warping.[5] In warping, a set of key points are determined by using face detection techniques. These key points' coordinates are shifted according to a warping strength parameter and the new intensity values are determined by using interpolation. Warping is local and compression independent. Its reversibility depends on the strength of the warping applied. It has been shown that while low warping

*This is the default color scale used to visualize radiance maps in the Radiance global illumination software.[1]

strength values make the method reversible it may not provide sufficient protection against both human observers and face recognition algorithms. Using high values, on the other hand, may render the warped images irreversible. Furthermore, high warping values often result in visually disturbing face rendering.

Another related privacy protection approach is called morphing.[6] In morphing, the goal is to find an average face image between the source and the target faces according to a given interpolation level. The source face corresponds to the face of the individual whose identity must be preserved. The target face is any generic human face. The method first divides both images into Delaunay triangles[7] and transforms the vertices of the source image toward the vertices of the target image. The pixel intensities are also interpolated with respect to a second parameter. Morphing is compression and format independent. It is also reversible unless the source image is morphed perfectly to the target image and the target image is known. Its security can be ensured by encrypting the key points and randomizing the interpolation level and the pixel interpolation values for each triangle. However, as the algorithm begins with triangulating the face images, it may fail to work in cases where the faces are not captured from ideal angles.

Region based scrambling is another technique to protect privacy in video surveillance.[8] First, the region to be scrambled (ROI) is estimated. Next, the signs of the AC and DC coefficients of discrete cosine transform (DCT) are pseudorandomly inverted. For security and reversibility, the seed value of the pseudorandom number generator is encrypted. Although scrambling ensures that the protected region is unrecognizable (as it appears as random noise), it also prevents acquiring non-sensitive information from the scrambled region. Furthermore, the method is format/compression dependent.

Privacy protection can also be accomplished by removing the sensitive parts of the frames of a video. The removed parts create holes in the resulting frames. These holes can be filled with image in-painting techniques.[9] If the background of the frame is static then these holes can be filled with the information from the other frames. Otherwise, if the background is dynamic, the holes can be filled by using the information from the neighboring pixels.

Encrypting visual objects, such as shapes and textures in an image content that is partitioned in hierarchical trees can be performed with a method called Secure Shape and Texture SPIHT (SecST-SPIHT where SPIHT is an abbreviation for Set Partitioning in Hierarchical Trees).[10] SecST-SPIHT encrypts shapes and textures and ensures that reconstruction is not possible without knowing the decryption key. It is reversible but it does not permit non-private information to be extracted from a video as the output does not contain any meaningful visual information.

A recent work by Erdélyi *et al.*, called adaptive cartooning, converts an image into an abstracted cartoon-like version.[11] The algorithm's main steps are smoothing and edge enhancement. The areas with similar color values are smoothed and the areas with color discontinuities (edges) are accentuated. This method can be applied to an ROI or the whole image. Thus it can be classified as both a local and global method. However, it is irreversible.

3. FALSE COLOR BASED PRIVACY PROTECTION

The core of the proposed method involves representing images in a different color scale to distort private information while preserving intelligibility. The rationale for this is based on the fact that the human visual system is particularly tuned to recognize faces when seen under standard illumination. If this illumination changes, for example by moving the light source such that it illuminates a face from the bottom rather than the top, it becomes difficult to recognize even familiar faces. Furthermore, earlier research suggests that if faces are represented in nonmonotonic color scales, it becomes much harder for people to recognize them.[3]

Based on these ideas, we first transform an image (containing faces) using a point-wise compression or expansion function. The purpose of this step is to bring together or spread apart the intensity distribution of the pixel values. We then transform the resulting image into a different color scale. In the following subsections, both the compression/expansion algorithms and the color scales are explained in more details.

3.1 Compression/Expansion Stage

The purpose of compression/expansion stage is to induce a change in the intensity distribution of an input image. We have experimented with logarithmic and sigmoidal functions as compressive transformations and histogram equalization as an expansion transformation. During the experiments, we have also tested a no-transformation case (abbreviated by **NOP**) to understand whether this initial step has a significant influence on the results. All of these operations are applied on the intensity image which is computed from an RGB image as follows†:

$$Y = 0.216R + 0.7152G + 0.0722B. \quad (1)$$

Logarithmic scaling (LOG): Logarithmic scaling scales the logarithm values of the intensity image to the $[0, 1]$ range:

$$f_{log}(Y) = \frac{\log(Y + \epsilon) - \log(Y_{min} + \epsilon)}{\log(Y_{max} + \epsilon) - \log(Y_{min} + \epsilon)}. \quad (2)$$

Here, a small value ($\epsilon = 10^{-6}$) is added to intensity values to avoid singularity for black pixels.[12]

Sigmoidal compression (SIG): This compression technique, inspired from the photographic tone mapping operator,[13] compresses the intensity values through an S-shape function applied after an initial intensity scaling:

$$f_{sig}(Y) = \frac{\alpha Y/\bar{Y}}{1 + \alpha Y/\bar{Y}}, \quad (3)$$

where α denotes a user-defined key value and $\bar{Y}$ is the log-average intensity value computed as:

$$\bar{Y} = \exp\left(\frac{1}{N}\sum_{x,y}\log(Y(x, y) + \epsilon)\right). \quad (4)$$

For the current experiments, $\alpha = 0.18$ and $\epsilon = 10^{-6}$ values are used. For both logarithmic and sigmoidal scaling the color mapping algorithm is defined in Algorithm 1, where one needs to substitute f_{log} or f_{sig} for f. In this algorithm, $\mathbf{C_{m,n}}$ is the false color value found in the given palette:

Algorithm 1: Color selection algorithm for logarithmic and sigmoidal compression

$Y' = f(Y)$
for $i = 0 \rightarrow 255$ **do**
  $bin[i] = \frac{i}{255}(Y'_{max} - Y'_{min})$
end
for ***each*** pixel $Y'_{m,n} \in Y'$ **do**
  find k **where** $|Y'_{m,n} - bin[k]|$ *is minimum*
  $\mathbf{C_{m,n}} = PALETTE[k]$
end

Histogram Equalization (HIS): Histogram equalization redistributes the intensity values such that each bin contains equal number of pixels.[14] Instead of computing histograms, bin boundaries and palette indices based on the distance of the luminance values to these boundaries are directly computed as shown in Algorithm 2.

3.2 Color Scale Selection

Following the intensity compression stage, the colors of an image are then scaled according to one of the four color scales presented in Figure 1 and summarized below:

Rainbow scale (RBS): RBS is also called the spectral scale since the ordering of the colors is roughly based on their wavelength. The palette of this scale is generally produced by varying the hue attribute in a color space such as HSV and keeping the other attributes constant. RBS has a nonmonotonic perceived intensity progression.

† We do not use the term *luminance* here as the input images are in a non-linear and uncalibrated color space.

Algorithm 2: Color selection algorithm for histogram equalization

$Y_s = sort(Y)$ *in ascending order*
$l = length(Y_s)$
for $i = 0 \rightarrow 255$ **do**
    $bin[i] = Y_s[l \times \frac{i}{255}]$
end
for ***each*** pixel $Y_{m,n} \in Y$ **do**
    find k **where** $|Y_{m,n} - bin[k]|$ *is minimum*
    $\mathbf{C_{m,n}} = PALETTE[k]$
end

Figure 1: Color scales used in this study (see Appendix for numerical values).

Heated-body scale (HBS): In HBS, colors progress from black to white while passing through orange and yellow. The advantage of this scale is attributed to the fact that the human visual system is mostly sensitive to luminance changes in that portion of the spectrum. The perceived intensity increase monotonically for this scale.

Radiance default color scale (DEF): This is the default false coloring scale used in the Radiance global illumination software.[1] It was designed to maximize the number of named colors while still depicting a progression from cold to hot.

Linearized optimal color scale (LOCS): LOCS is designed to create a maximum number of just noticeable differences (JNDs) while preserving a natural order.[15] This scale is perceptually linearized (numerical color differences correspond to perceived color differences) and monotonically increasing in perceived intensity.

RBS color scale was selected because it is commonly used for visualization, although it also has a bad reputation.[16] HBS was selected as another commonly used scale, in which the perceived intensity values increase monotonically across the scale. LOCS was selected because it is both monotonic and perceptually linear. Finally, DEF was selected as it is the default color scale in a commonly used light simulation program, Radiance.[1] The color palettes of these four color scales can be found in the Appendix.

4. EVALUATION

In this paper, we performed both objective and subjective evaluations using 100 face images from the publicly available FERET face recognition dataset.[4] Figure 2 presents example images from the dataset. Objective evaluation relied on three face recognition algorithms implemented in the evaluation framework by Korshunov *et al.*[2] In subjective evaluation, we employed 50 subjects in online study.

4.1 Objective Evaluation

For objective evaluation, each face image was false colored using the combinations of the three point transformations functions plus a no-transformation condition and four color scales resulting in total 16 visualizations per face. The resulted


Figure 2: Sample images from FERET dataset.

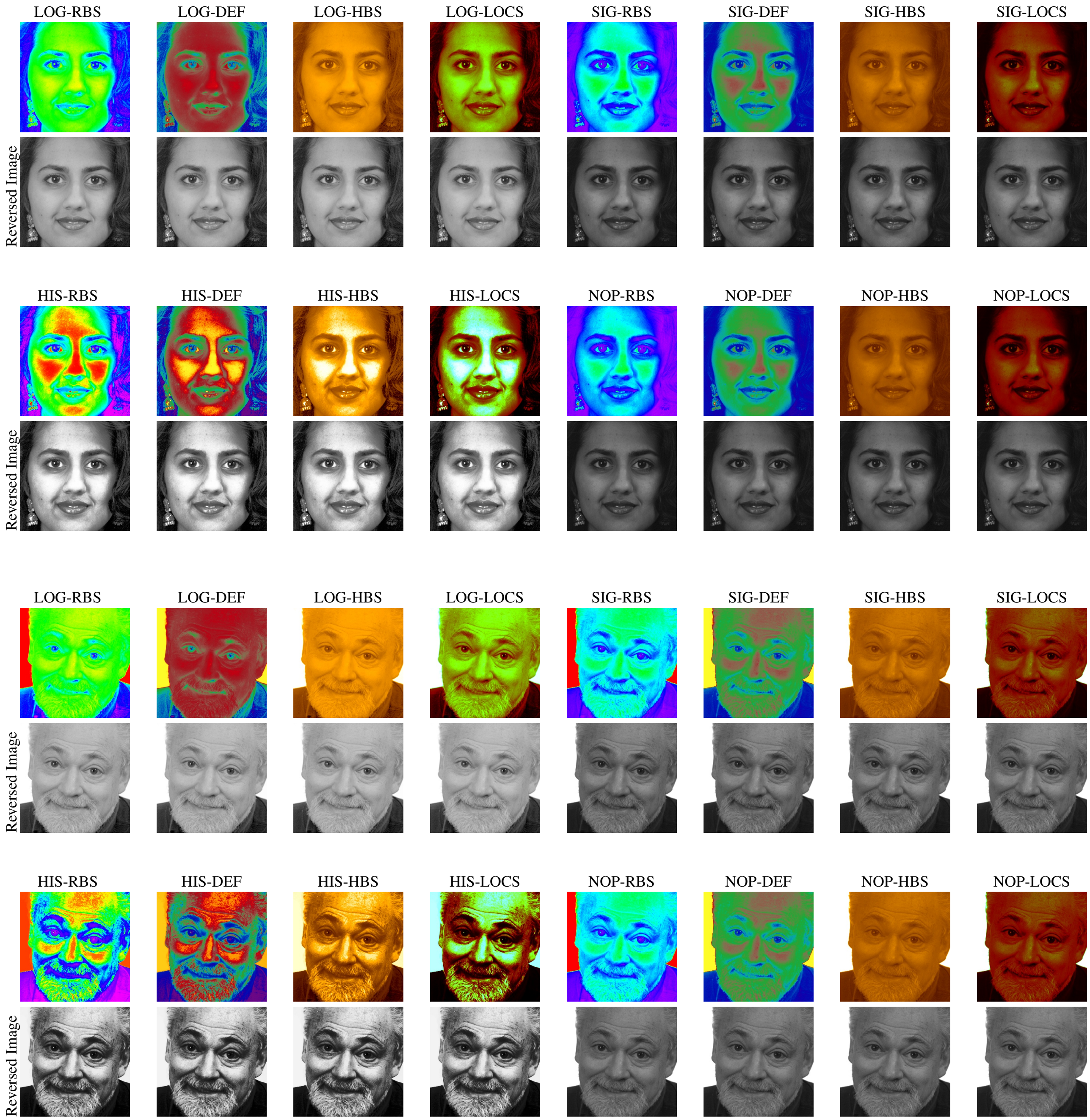

Figure 3: False colored image results for the two sample images.

false colored sample images are presented in Figure 3. To evaluate the recognizability of these false color visualizations, we used objective evaluation framework,[2] which utilizes three face recognition algorithms implemented in OpenCV[‡] The face recognition algorithms are the principal component analysis (PCA) referred to as 'Eigen',[17] linear discriminant analysis (LDA) referred to as 'Fisher',[18] and local binary patterns referred to as 'LBPH' algorithm.[19]

[‡]http://opencv.willowgarage.com/wiki/

4.1.1 Results

The visual inspection of Figure 3, showing different false colored images, reveal that not all compression type/color palette combination are equally effective. For example, the faces in the images obtained by using the HBS and LOCS remain mostly recognizable. This can be attributed to the fact that these color scales have a monotonic perceived intensity variation. However, the RBS and the DEF appear to apply strong enough distortions to faces, making them hard to recognize.

These visual observations are supported by the quantitative results that are obtained by using the above mentioned objective framework. Table 1 reports the face recognition accuracy obtained by running three different face recognition algorithms on all false colored images from the dataset. In this table, the lower accuracy numbers indicate a higher degree of privacy protection against face recognition algorithms. It can be seen that, on average, the 'LBPH' method is the most successful in recognizing false colored face images. However, for HIS-DEF combination, even 'LBPH' recognition shows a low accuracy of 0.11, which means that out of 100 face images in the dataset, only 11 were correctly recognized by the algorithm. In general, the DEF color scale is the most effective in privacy protection, since it reduces the accuracy rates irrespective of the applied point transformation. Following DEF, RBS color scale is found to be the second most effective. The other two color scales, HBS and LOCS, are both ineffective against recognition algorithms, leading to high accuracy ratings.

Similar trends can be observed for 'Eigen' and 'Fisher' face recognition algorithms. However, the accuracy ratings of both of these algorithms are generally lower than the LBPH-based face recognition algorithm. For both algorithms LOG-RBS, SIG-DEF, and NOP-DEF methods yield a 0 accuracy value.

Based on the results in Table 1, it can be argued that the color scale is the critical factor that strongly influences the face recognition accuracy for the tested face recognition algorithms. It shows that a point transformation applied prior to the color mapping has little affect on the accuracy of the algorithms and, hence, has little contribution to privacy protection.

We also compare the obtained accuracy ratings with two methods from the literature, namely blurring and warping (Table 2). The lowest accuracy for these two methods is obtained for a blur kernel size of 55, which leads to accuracy value 0.14 of 'LBPH' recognition and significantly higher for other recognition methods. However, blurring is not only computationally more expensive than the proposed false coloring algorithm, but it is also irreversible when such a large kernel size of 55 is applied. False colored images can be reversed to obtain the images that are very close to originals (see the second rows for each sample face in Figure 3). The slight intensity differences between the originals and the reversed images mainly due to the compression functions.

Palette / Compression	LBPH				Eigen				Fisher			
	RBS	**DEF**	**HBS**	**LOCS**	**RBS**	**DEF**	**HBS**	**LOCS**	**RBS**	**DEF**	**HBS**	**LOCS**
LOG	0.27	0.14	0.75	0.76	**0.00**	0.01	0.44	0.49	**0.00**	0.01	0.44	0.49
SIG	0.41	0.14	0.78	0.50	0.01	**0.00**	0.61	0.46	0.01	**0.00**	0.61	0.46
HIS	0.19	**0.11**	0.87	0.69	0.05	0.04	0.59	0.67	0.05	0.04	0.58	0.66
NOP	0.46	0.13	0.76	0.44	0.01	**0.00**	0.60	0.37	0.01	**0.00**	0.59	0.36

Table 1: Face recognition accuracy rates results for false colored faces. The lower the value, the better the performance.

	LBPH		Eigen		Fisher	
Warping	Strength level = 3	Strength level = 13	Strength level = 3	Strength level = 13	Strength level = 3	Strength level = 13
	0.64	0.90	0.68	0.89	0.68	0.89
Blurring	Kernel size = 5	Kernel size = 55	Kernel size = 5	Kernel size = 55	Kernel size = 5	Kernel size = 55
	0.72	**0.14**	0.89	0.79	0.89	0.79

Table 2: Face recognition accuracy rates for warping and blurring. The lower the value, the better the performance.

4.2 Subjective Evaluation

A good privacy protection algorithm should provide effective protection not only against machines but also against human observers. We conducted online-based subjective experiments to evaluate this aspect of the proposed privacy protection method. For subjective evaluation, we used 10 faces from the FERET100 dataset. In our experimental design, we used a similar approach to that proposed by Rogowitz and Kalvin.[3] In our web-based implementation, we asked participants to rate the recognizability of the false color visualizations with respect to the original image. The participants could see the

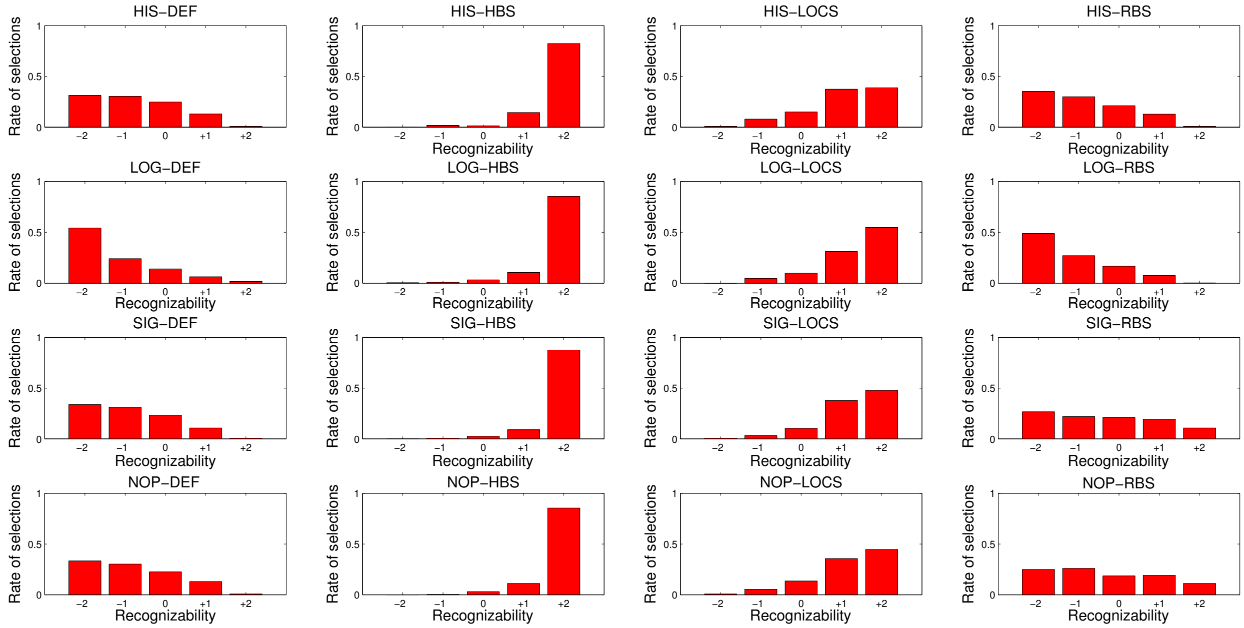

Figure 4: Cumulative results of the subjective experiments. The x-axis represents the recognizability values and the y-axis represents participants' normalized selection counts.

original image on the left and the false color images in random order appearing as a 4 by 4 grid on the right. Under each false color image there was a drop-down list with the following options:

+2: Very likely to be recognizable

+1: Likely to be recognizable

0: May or may not be recognizable

-1: Unlikely to be recognizable

-2: Very unlikely to be recognizable

The experiment was comprised of 10 sessions, whereby a different input face image was used in each session. Each session ended when a participant indicated his or her responses for all of the 16 visualizations. The order of the sessions and the visualizations in each session were randomized to avoid any order-specific bias. The experiment had a web interface and therefore each participant took the experiment using his or her own computer system. The duration of a single experiment was approximately $15 - 20$ minutes. A total of 50 naïve subjects (36 males and 14 females) completed all sessions in full and their results were analyzed.

4.2.1 Results

The cumulative results of the subjective experiment are depicted in Figure 4. Each histogram in this figure indicates the responses for a single visualization method aggregated over all participants and face images. The y-axis is normalized to indicate the rate of selections. As can be seen from this figure, both DEF and RBS scales gave rise to right-skewed distributions whereas HBS and LOCS produced left-skewed ones. This suggests that the former two color scales are found less likely to be recognizable whereas the latter two are more likely to be recognizable. Similar to the results of objective evaluation, for all color scales, the compression/expansion methods do not seem to have a significant influence.

In order to obtain a global score for all methods, responses with values -2, -1,$+1$, and $+2$ were added together to obtain one single value. Therefore, a global score with large negative value means that the corresponding method produces less recognizable faces. The global scores computed for all false color protection methods are shown in Table 3, where

	DEF	RBS	LOCS	HBS
LOG	$\mathbf{-352}$	$\mathbf{-341}$	407	472
SIG	-267	-93	408	479
HIS	-238	-258	337	475
NOP	-249	-103	370	481

Table 3: The global scores for each method. More negative scores indicate less recognizable methods. For example, LOG-DEF was rated as -2 or -1 352 times out of a total of 500 ratings.

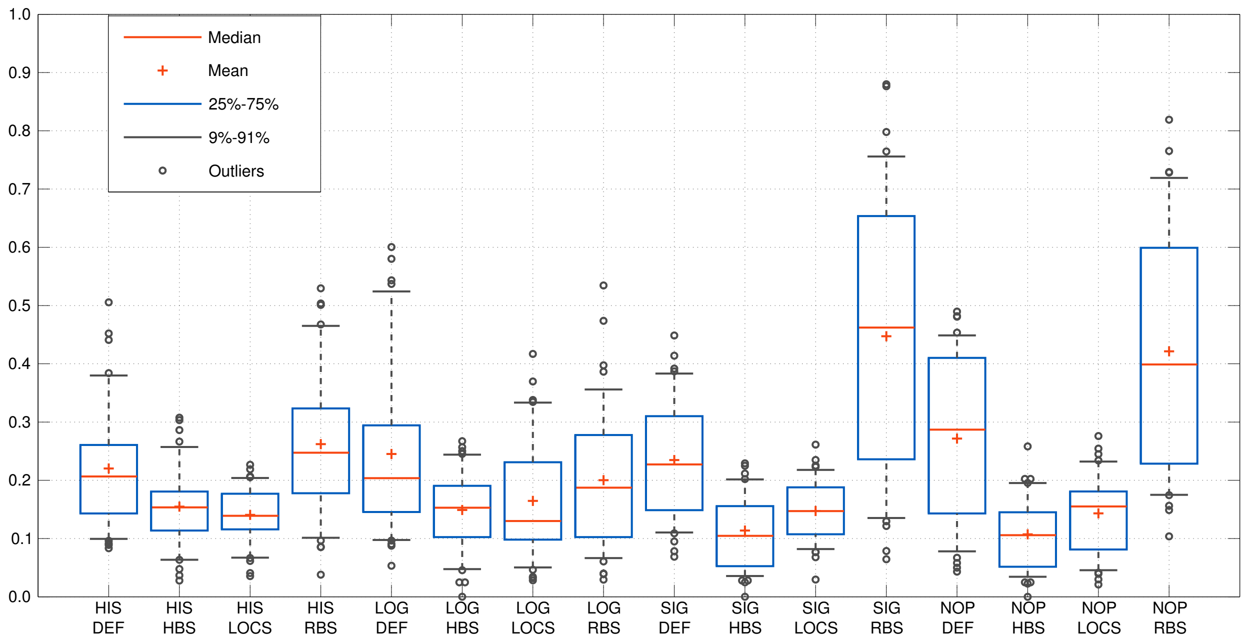

Figure 5: The distribution of Bhattacharya distances between the per-face histograms for each visualization method. The smaller the values of a distribution are the more consistent the corresponding method is for different faces.

the two largest negative scores are highlighted in bold. The table shows that LOG-DEF and LOG-RBS scales produce the least recognizable faces, while LOCS and HBS color scales lead to the easiest recognizable faces irrespective of the prior compression transformation.

To understand whether a given method's preferences vary across faces, we conducted further analysis of the subjective results. We computed the Bhattacharya distances between pairs of histograms that are obtained for different faces. For 10 faces used in the subjective study, we have $C(10, 2) = 45$ pairs, resulting in 45 different distance values for each of 16 methods. These distances are plotted in Figure 5, where different false color methods are shown in x-axis and and Bhattacharya distances in y-axis. In this figure, the smaller the values of a distribution, the more consistent the corresponding method is for different faces. However, a method can be consistently recognizable or consistently unrecognizable. The two most unrecognizable methods, similarly to objective evaluations, are LOG-DEF and LOG-RBS, with the latter varying slightly less across different faces. Hence, we conclude that LOG-RBS is the winner method in the subjective experiments with LOG-DEF being the close second.

The conclusion that the LOG-RBS method was found to produce the least recognizable images may be explained as follows. The logarithmic compression clumps together different intensity values more so than the other compression methods. Furthermore, the yellow colors dominate the RBS color space which has a masking effect over other hues due to the higher sensitivity of the human visual system to yellow. Finally, yellow has the smallest number of saturation steps which make it difficult to distinguish small saturation variations.[20] These properties of LOG-RBS may have resulted in certain facial features to be lost when a face is visualized using this method, rendering it less recognizable.

We also investigated the correlation between the rankings of the user study and the rankings obtained by using the face recognition algorithms. For this purpose, we computed Spearman's rank correlation coefficient,[21] which is a commonly

Figure 6: Interpolation between an original image and its false color visualization. The numbers indicate the weights given to the false color result. LOG-DEF is used as the visualization method.

used measure to compare ranked variables. We obtained a correlation value of $\rho = 0.8645$ with LBPH and $\rho = 0.8195$ with 'Eigen' and 'Fisher' algorithms. Such high correlation values indicate that false colored faces are perceived similarly by both human observers and face recognition algorithms, which is an important finding, since for more typical distortions (blurring or pixelization) the perception by humans and computers is different.[22]

Finally, we show the amount of privacy protection by using false colors is adjustable as the final result can be computed by interpolating the false color image with the original with different degrees of interpolation. For some applications where intelligibility is more important than privacy, a lower weight can be given to the false colored result to produce more intelligible images as shown in Figure 6.

5. CONCLUSION AND FUTURE WORK

Privacy protection in video surveillance is an important problem, and it will become even more important, as video surveillance is gains in popularity. However, simple methods for protecting privacy are not sufficient as they do not contain all the desired attributes that is expected from a good privacy protection algorithm. Privacy protected videos must be reversible if the need arises to view them as unprotected (e.g., during a criminal investigation). Furthermore, protected videos should not prohibit non-private statistics to be extracted. Also, the protected content should not be visually disturbing as it is the case with some of the existing privacy protection methods, such as scrambling and warping. Perhaps most importantly, the protection must be continuous: that is faces even in a single frame of a video should not remain unprotected. The algorithms that rely on computer vision techniques may therefore be vulnerable to this problem: if an algorithm fails to detect a sensitive region, it will remain unprotected.

This paper proposed false color based method, which aims to achieve the balance between the above mentioned desired attributes. The method is reversible since the compression and color scale tables can be inverted and is secure because these tables can be encrypted using a private key. The false colored representations do not prohibit collecting non-private information (for instance one can still count the number of people in an area without knowing their identities). And since the method does not rely on computer vision, it therefore is not affected by potential failures of detection or tracking algorithms.

The objective and subjective evaluations show that DEF and RBS color scales are the most suitable for privacy protection for both use cases, when face recognition algorithms and human subjects are the main observers of the protected images. Also, compression/expansion schemes demonstrate a significantly less effect on the strength of privacy protection compared to the color scales.

Several future research directions are possible. Firstly, the proposed algorithm can be evaluated using crowdsourcing. This would involve input from a large number of participants from very different backgrounds. The experimental task can be varied: instead of directly asking the degree of recognizability, one can design a task that indirectly evaluates this attribute. For example, one can ask whether a person whose images was previously shown appears in a given video clip. Such a design is likely to represent a more realistic surveillance scenario. Finally, the design of other compression algorithms and color palettes that are customized for protecting privacy can be an studied.

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APPENDIX: COLOR PALETTES

DEF											
	R	**G**	**B**		**R**	**G**	**B**		**R**	**G**	**B**
0	111	8	132	**86**	18	174	81	**172**	159	34	40
1	108	7	133	**87**	20	174	77	**173**	159	33	39
2	105	7	134	**88**	21	173	73	**174**	160	32	38
3	102	6	136	**89**	22	172	69	**175**	160	31	37
4	98	6	137	**90**	24	172	66	**176**	161	29	37
5	93	5	139	**91**	26	171	63	**177**	161	28	36
6	89	4	141	**92**	28	170	60	**178**	162	27	35
7	84	3	143	**93**	30	169	58	**179**	162	26	34
8	79	2	145	**94**	32	168	57	**180**	163	25	33
9	74	1	148	**95**	34	167	56	**181**	163	24	33
10	68	0	150	**96**	37	166	55	**182**	164	23	32
11	63	0	153	**97**	40	165	54	**183**	165	22	31
12	57	0	155	**98**	42	164	54	**184**	165	21	31
13	52	0	157	**99**	45	163	54	**185**	168	18	29
14	46	0	160	**100**	48	162	55	**186**	170	16	28
15	41	0	162	**101**	52	160	55	**187**	172	13	26
16	36	0	164	**102**	55	158	56	**188**	175	11	25
17	31	0	166	**103**	58	157	57	**189**	177	9	24
18	26	0	168	**104**	62	155	57	**190**	180	7	23
19	22	0	170	**105**	66	153	59	**191**	183	5	22
20	18	0	172	**106**	69	152	60	**192**	185	3	21
21	14	2	174	**107**	73	150	61	**193**	188	2	21
22	11	4	175	**108**	77	148	63	**194**	191	1	20
23	8	7	176	**109**	81	146	64	**195**	194	0	19
24	7	9	177	**110**	84	144	66	**196**	197	0	19
25	6	11	177	**111**	88	142	67	**197**	199	0	18
26	5	13	178	**112**	92	139	69	**198**	202	0	17
27	4	16	178	**113**	96	137	70	**199**	205	0	17
28	3	18	179	**114**	99	135	72	**200**	207	0	16
29	2	21	180	**115**	103	133	73	**201**	210	2	16
30	1	24	180	**116**	107	131	75	**202**	213	3	15
31	1	28	181	**117**	110	128	76	**203**	215	6	14
32	0	31	181	**118**	113	126	77	**204**	217	8	13
33	0	35	182	**119**	117	124	78	**205**	219	11	13
34	0	38	182	**120**	120	121	79	**206**	220	13	12
35	0	42	183	**121**	123	119	80	**207**	222	17	11
36	0	46	184	**122**	126	117	80	**208**	224	20	11
37	0	50	184	**123**	128	114	81	**209**	226	24	10
38	0	54	184	**124**	131	112	81	**210**	227	28	9
39	0	58	185	**125**	133	110	81	**211**	229	32	8
40	0	63	185	**126**	135	108	80	**212**	231	37	7
41	0	67	186	**127**	136	106	80	**213**	232	42	6
42	0	71	186	**128**	137	105	80	**214**	234	47	5
43	0	76	186	**129**	138	104	79	**215**	236	52	5
44	0	80	187	**130**	139	102	79	**216**	237	57	4
45	0	84	187	**131**	140	101	79	**217**	239	63	3
46	0	89	187	**132**	141	100	78	**218**	240	68	2
47	0	93	187	**133**	142	98	78	**219**	242	74	2
48	1	97	187	**134**	143	96	77	**220**	243	79	1
49	1	102	187	**135**	144	95	76	**221**	245	85	0
50	1	106	187	**136**	144	93	76	**222**	246	91	0
51	2	110	187	**137**	145	92	75	**223**	247	96	0
52	2	114	187	**138**	146	90	74	**224**	248	102	0
53	3	118	186	**139**	146	89	73	**225**	250	108	0
54	3	122	186	**140**	147	87	73	**226**	251	113	0
55	4	126	186	**141**	148	85	72	**227**	252	118	0
56	4	130	185	**142**	148	84	71	**228**	253	123	0
57	4	133	185	**143**	149	82	70	**229**	254	128	0
58	5	137	184	**144**	149	80	69	**230**	254	133	0
59	5	140	183	**145**	150	79	68	**231**	255	138	0
60	6	143	182	**146**	150	77	67	**232**	255	143	1
61	6	146	181	**147**	151	75	66	**233**	255	148	2
62	6	149	180	**148**	151	73	65	**234**	255	154	3
63	7	151	179	**149**	151	72	64	**235**	255	159	4
64	7	154	178	**150**	152	70	63	**236**	255	165	6
65	7	156	177	**151**	152	68	62	**237**	255	170	7
66	8	158	175	**152**	153	66	61	**238**	255	176	9
67	8	161	172	**153**	153	65	60	**239**	255	181	11
68	9	163	169	**154**	153	63	59	**240**	255	187	13
69	9	165	165	**155**	154	61	58	**241**	255	192	15
70	9	167	161	**156**	154	60	57	**242**	255	198	17
71	9	169	157	**157**	154	58	56	**243**	255	203	20
72	10	170	153	**158**	154	56	55	**244**	255	208	22
73	10	172	148	**159**	155	55	54	**245**	255	213	24
74	10	173	143	**160**	155	53	53	**246**	255	218	26
75	11	174	138	**161**	155	51	51	**247**	255	223	28
76	11	174	133	**162**	156	50	50	**248**	255	227	30
77	11	175	127	**163**	156	48	49	**249**	255	232	32
78	12	175	122	**164**	156	46	48	**250**	255	236	34
79	12	176	117	**165**	157	45	47	**251**	254	240	35
80	13	176	111	**166**	157	43	46	**252**	254	243	37
81	14	176	106	**167**	157	42	45	**253**	254	246	38
82	14	176	101	**168**	158	40	44	**254**	254	249	39
83	15	175	95	**169**	158	39	43	**255**	254	252	40
84	16	175	90	**170**	158	37	42				
85	17	175	86	**171**	159	36	41				

HBS											
	R	**G**	**B**		**R**	**G**	**B**		**R**	**G**	**B**
0	0	0	0	**86**	163	84	0	**172**	244	150	0
1	35	0	0	**87**	165	85	0	**173**	244	150	0
2	52	0	0	**88**	165	85	0	**174**	245	151	0
3	60	0	0	**89**	166	86	0	**175**	247	153	0
4	63	1	0	**90**	166	86	0	**176**	247	153	0
5	64	2	0	**91**	166	86	0	**177**	248	154	0
6	68	5	0	**92**	168	87	0	**178**	250	155	0
7	69	6	0	**93**	168	87	0	**179**	251	156	0
8	72	8	0	**94**	170	89	0	**180**	251	156	0
9	74	10	0	**95**	170	89	0	**181**	253	158	0
10	77	12	0	**96**	171	90	0	**182**	255	159	0
11	78	14	0	**97**	171	90	0	**183**	255	159	0
12	81	16	0	**98**	173	91	0	**184**	255	160	0
13	83	17	0	**99**	173	91	0	**185**	255	161	0
14	85	19	0	**100**	174	93	0	**186**	255	163	0
15	86	20	0	**101**	174	93	0	**187**	255	163	0
16	89	22	0	**102**	176	94	0	**188**	255	164	0
17	91	24	0	**103**	176	94	0	**189**	255	165	0
18	92	25	0	**104**	177	95	0	**190**	255	167	0
19	94	26	0	**105**	177	95	0	**191**	255	167	0
20	95	28	0	**106**	179	96	0	**192**	255	168	0
21	98	30	0	**107**	179	96	0	**193**	255	169	0
22	100	31	0	**108**	180	98	0	**194**	255	169	0
23	102	33	0	**109**	182	99	0	**195**	255	170	0
24	103	34	0	**110**	182	99	0	**196**	255	172	0
25	105	35	0	**111**	183	100	0	**197**	255	173	0
26	106	36	0	**112**	183	100	0	**198**	255	173	0
27	108	38	0	**113**	185	102	0	**199**	255	174	0
28	109	39	0	**114**	185	102	0	**200**	255	175	0
29	111	40	0	**115**	187	103	0	**201**	255	177	0
30	112	42	0	**116**	187	103	0	**202**	255	178	0
31	114	43	0	**117**	188	104	0	**203**	255	179	0
32	115	44	0	**118**	188	104	0	**204**	255	181	0
33	117	45	0	**119**	190	105	0	**205**	255	181	0
34	119	47	0	**120**	191	107	0	**206**	255	182	0
35	119	47	0	**121**	191	107	0	**207**	255	183	0
36	120	48	0	**122**	193	108	0	**208**	255	184	0
37	122	49	0	**123**	193	108	0	**209**	255	187	7
38	123	51	0	**124**	194	109	0	**210**	255	188	10
39	125	52	0	**125**	196	110	0	**211**	255	189	14
40	125	52	0	**126**	196	110	0	**212**	255	191	18
41	126	53	0	**127**	197	112	0	**213**	255	192	21
42	128	54	0	**128**	197	112	0	**214**	255	193	25
43	129	56	0	**129**	199	113	0	**215**	255	195	29
44	129	56	0	**130**	200	114	0	**216**	255	197	36
45	131	57	0	**131**	200	114	0	**217**	255	198	40
46	132	58	0	**132**	202	116	0	**218**	255	200	43
47	134	59	0	**133**	202	116	0	**219**	255	202	51
48	134	59	0	**134**	204	117	0	**220**	255	204	54
49	136	61	0	**135**	205	118	0	**221**	255	206	61
50	137	62	0	**136**	205	118	0	**222**	255	207	65
51	137	62	0	**137**	207	119	0	**223**	255	210	72
52	139	63	0	**138**	208	121	0	**224**	255	211	76
53	139	63	0	**139**	208	121	0	**225**	255	214	83
54	140	65	0	**140**	210	122	0	**226**	255	216	91
55	142	66	0	**141**	211	123	0	**227**	255	219	98
56	142	66	0	**142**	211	123	0	**228**	255	221	105
57	143	67	0	**143**	213	124	0	**229**	255	223	109
58	143	67	0	**144**	214	126	0	**230**	255	225	116
59	145	68	0	**145**	214	126	0	**231**	255	228	123
60	145	68	0	**146**	216	127	0	**232**	255	232	134
61	146	70	0	**147**	217	128	0	**233**	255	234	142
62	146	70	0	**148**	217	128	0	**234**	255	237	149
63	148	71	0	**149**	219	130	0	**235**	255	239	156
64	148	71	0	**150**	221	131	0	**236**	255	240	160
65	149	72	0	**151**	221	131	0	**237**	255	243	167
66	149	72	0	**152**	222	132	0	**238**	255	246	174
67	151	73	0	**153**	224	133	0	**239**	255	248	182
68	151	73	0	**154**	224	133	0	**240**	255	249	185
69	153	75	0	**155**	225	135	0	**241**	255	252	193
70	153	75	0	**156**	227	136	0	**242**	255	253	196
71	154	76	0	**157**	227	136	0	**243**	255	255	204
72	154	76	0	**158**	228	137	0	**244**	255	255	207
73	154	76	0	**159**	230	138	0	**245**	255	255	211
74	156	77	0	**160**	230	138	0	**246**	255	255	218
75	156	77	0	**161**	231	140	0	**247**	255	255	222
76	157	79	0	**162**	233	141	0	**248**	255	255	225
77	157	79	0	**163**	233	141	0	**249**	255	255	229
78	159	80	0	**164**	234	142	0	**250**	255	255	233
79	159	80	0	**165**	236	144	0	**251**	255	255	236
80	159	80	0	**166**	236	144	0	**252**	255	255	240
81	160	81	0	**167**	238	145	0	**253**	255	255	244
82	160	81	0	**168**	239	146	0	**254**	255	255	247
83	162	82	0	**169**	241	147	0	**255**	255	255	255
84	162	82	0	**170**	241	147	0				
85	163	84	0	**171**	242	149	0				

Table 4: Color palettes for DEF and HBS color maps.

LOCS												RBS											
	R	**G**	**B**		**R**	**G**	**B**		**R**	**G**	**B**		**R**	**G**	**B**		**R**	**G**	**B**		**R**	**G**	**B**
0	0	0	0	**86**	135	6	0	**172**	135	200	0	**0**	251	0	255	**86**	0	178	255	**172**	96	255	0
1	0	0	0	**87**	135	8	0	**173**	135	203	0	**1**	246	0	255	**87**	0	183	255	**173**	101	255	0
2	0	0	0	**88**	135	9	0	**174**	135	205	0	**2**	241	0	255	**88**	0	188	255	**174**	106	255	0
3	1	0	0	**89**	135	10	0	**175**	135	210	0	**3**	236	0	255	**89**	0	193	255	**175**	111	255	0
4	2	0	0	**90**	135	11	0	**176**	135	214	0	**4**	231	0	255	**90**	0	198	255	**176**	116	255	0
5	2	0	0	**91**	135	13	0	**177**	135	218	0	**5**	226	0	255	**91**	0	203	255	**177**	121	255	0
6	3	0	0	**92**	135	13	0	**178**	135	222	0	**6**	221	0	255	**92**	0	208	255	**178**	126	255	0
7	3	0	0	**93**	135	15	0	**179**	135	226	0	**7**	216	0	255	**93**	0	213	255	**179**	131	255	0
8	4	0	0	**94**	135	17	0	**180**	135	231	0	**8**	211	0	255	**94**	0	218	255	**180**	136	255	0
9	5	0	0	**95**	135	17	0	**181**	135	236	0	**9**	206	0	255	**95**	0	223	255	**181**	141	255	0
10	5	0	0	**96**	135	19	0	**182**	135	239	0	**10**	201	0	255	**96**	0	228	255	**182**	146	255	0
11	6	0	0	**97**	135	21	0	**183**	135	244	0	**11**	196	0	255	**97**	0	233	255	**183**	151	255	0
12	7	0	0	**98**	135	22	0	**184**	135	249	0	**12**	191	0	255	**98**	0	238	255	**184**	156	255	0
13	7	0	0	**99**	135	23	0	**185**	135	254	0	**13**	186	0	255	**99**	0	243	255	**185**	161	255	0
14	8	0	0	**100**	135	25	0	**186**	135	255	1	**14**	181	0	255	**100**	0	248	255	**186**	166	255	0
15	9	0	0	**101**	135	26	0	**187**	135	255	5	**15**	176	0	255	**101**	0	253	255	**187**	171	255	0
16	9	0	0	**102**	135	27	0	**188**	135	255	10	**16**	171	0	255	**102**	0	255	253	**188**	176	255	0
17	10	0	0	**103**	135	29	0	**189**	135	255	15	**17**	166	0	255	**103**	0	255	248	**189**	181	255	0
18	11	0	0	**104**	135	31	0	**190**	135	255	20	**18**	161	0	255	**104**	0	255	243	**190**	186	255	0
19	12	0	0	**105**	135	32	0	**191**	135	255	23	**19**	156	0	255	**105**	0	255	238	**191**	191	255	0
20	13	0	0	**106**	135	33	0	**192**	135	255	28	**20**	151	0	255	**106**	0	255	233	**192**	196	255	0
21	14	0	0	**107**	135	35	0	**193**	135	255	33	**21**	146	0	255	**107**	0	255	228	**193**	201	255	0
22	15	0	0	**108**	135	36	0	**194**	135	255	38	**22**	141	0	255	**108**	0	255	223	**194**	206	255	0
23	16	0	0	**109**	135	38	0	**195**	135	255	43	**23**	136	0	255	**109**	0	255	218	**195**	211	255	0
24	17	0	0	**110**	135	40	0	**196**	135	255	45	**24**	131	0	255	**110**	0	255	213	**196**	216	255	0
25	18	0	0	**111**	135	42	0	**197**	135	255	49	**25**	126	0	255	**111**	0	255	208	**197**	221	255	0
26	19	0	0	**112**	135	44	0	**198**	135	255	54	**26**	121	0	255	**112**	0	255	203	**198**	226	255	0
27	20	0	0	**113**	135	46	0	**199**	135	255	59	**27**	116	0	255	**113**	0	255	198	**199**	231	255	0
28	21	0	0	**114**	135	47	0	**200**	135	255	65	**28**	111	0	255	**114**	0	255	193	**200**	236	255	0
29	22	0	0	**115**	135	49	0	**201**	135	255	70	**29**	106	0	255	**115**	0	255	188	**201**	241	255	0
30	23	0	0	**116**	135	51	0	**202**	135	255	74	**30**	101	0	255	**116**	0	255	183	**202**	246	255	0
31	25	0	0	**117**	135	52	0	**203**	135	255	80	**31**	96	0	255	**117**	0	255	178	**203**	251	255	0
32	26	0	0	**118**	135	54	0	**204**	135	255	84	**32**	91	0	255	**118**	0	255	173	**204**	255	254	0
33	27	0	0	**119**	135	56	0	**205**	135	255	90	**33**	86	0	255	**119**	0	255	168	**205**	255	249	0
34	28	0	0	**120**	135	57	0	**206**	135	255	95	**34**	81	0	255	**120**	0	255	163	**206**	255	244	0
35	30	0	0	**121**	135	59	0	**207**	135	255	98	**35**	76	0	255	**121**	0	255	158	**207**	255	239	0
36	31	0	0	**122**	135	62	0	**208**	135	255	104	**36**	71	0	255	**122**	0	255	153	**208**	255	234	0
37	33	0	0	**123**	135	63	0	**209**	135	255	110	**37**	66	0	255	**123**	0	255	148	**209**	255	229	0
38	34	0	0	**124**	135	65	0	**210**	135	255	116	**38**	61	0	255	**124**	0	255	143	**210**	255	224	0
39	35	0	0	**125**	135	67	0	**211**	135	255	120	**39**	56	0	255	**125**	0	255	138	**211**	255	219	0
40	37	0	0	**126**	135	69	0	**212**	135	255	125	**40**	51	0	255	**126**	0	255	133	**212**	255	214	0
41	39	0	0	**127**	135	72	0	**213**	135	255	131	**41**	47	0	255	**127**	0	255	128	**213**	255	209	0
42	40	0	0	**128**	135	73	0	**214**	135	255	137	**42**	42	0	255	**128**	0	255	123	**214**	255	204	0
43	43	0	0	**129**	135	76	0	**215**	135	255	144	**43**	37	0	255	**129**	0	255	118	**215**	255	199	0
44	45	0	0	**130**	135	78	0	**216**	135	255	149	**44**	32	0	255	**130**	0	255	113	**216**	255	194	0
45	46	0	0	**131**	135	80	0	**217**	135	255	154	**45**	27	0	255	**131**	0	255	108	**217**	255	189	0
46	49	0	0	**132**	135	82	0	**218**	135	255	158	**46**	22	0	255	**132**	0	255	103	**218**	255	184	0
47	51	0	0	**133**	135	84	0	**219**	135	255	165	**47**	17	0	255	**133**	0	255	98	**219**	255	179	0
48	53	0	0	**134**	135	87	0	**220**	135	255	172	**48**	12	0	255	**134**	0	255	93	**220**	255	174	0
49	54	0	0	**135**	135	88	0	**221**	135	255	179	**49**	7	0	255	**135**	0	255	88	**221**	255	169	0
50	56	0	0	**136**	135	90	0	**222**	135	255	186	**50**	2	0	255	**136**	0	255	83	**222**	255	164	0
51	58	0	0	**137**	135	93	0	**223**	135	255	191	**51**	0	3	255	**137**	0	255	78	**223**	255	159	0
52	60	0	0	**138**	135	95	0	**224**	135	255	198	**52**	0	8	255	**138**	0	255	73	**224**	255	154	0
53	62	0	0	**139**	135	98	0	**225**	135	255	203	**53**	0	13	255	**139**	0	255	68	**225**	255	150	0
54	64	0	0	**140**	135	101	0	**226**	135	255	211	**54**	0	18	255	**140**	0	255	63	**226**	255	145	0
55	67	0	0	**141**	135	103	0	**227**	135	255	216	**55**	0	23	255	**141**	0	255	58	**227**	255	140	0
56	69	0	0	**142**	135	106	0	**228**	135	255	224	**56**	0	28	255	**142**	0	255	53	**228**	255	135	0
57	71	0	0	**143**	135	107	0	**229**	135	255	232	**57**	0	33	255	**143**	0	255	48	**229**	255	130	0
58	74	0	0	**144**	135	110	0	**230**	135	255	240	**58**	0	38	255	**144**	0	255	43	**230**	255	125	0
59	76	0	0	**145**	135	113	0	**231**	135	255	248	**59**	0	43	255	**145**	0	255	38	**231**	255	120	0
60	80	0	0	**146**	135	115	0	**232**	135	255	254	**60**	0	48	255	**146**	0	255	33	**232**	255	115	0
61	81	0	0	**147**	135	118	0	**233**	135	255	255	**61**	0	53	255	**147**	0	255	28	**233**	255	110	0
62	84	0	0	**148**	135	121	0	**234**	140	255	255	**62**	0	58	255	**148**	0	255	23	**234**	255	105	0
63	86	0	0	**149**	135	124	0	**235**	146	255	255	**63**	0	63	255	**149**	0	255	18	**235**	255	100	0
64	89	0	0	**150**	135	127	0	**236**	153	255	255	**64**	0	68	255	**150**	0	255	13	**236**	255	95	0
65	92	0	0	**151**	135	129	0	**237**	156	255	255	**65**	0	73	255	**151**	0	255	8	**237**	255	90	0
66	94	0	0	**152**	135	133	0	**238**	161	255	255	**66**	0	78	255	**152**	0	255	3	**238**	255	85	0
67	97	0	0	**153**	135	135	0	**239**	168	255	255	**67**	0	83	255	**153**	2	255	0	**239**	255	80	0
68	100	0	0	**154**	135	138	0	**240**	172	255	255	**68**	0	88	255	**154**	7	255	0	**240**	255	75	0
69	103	0	0	**155**	135	141	0	**241**	177	255	255	**69**	0	93	255	**155**	12	255	0	**241**	255	70	0
70	106	0	0	**156**	135	144	0	**242**	182	255	255	**70**	0	98	255	**156**	17	255	0	**242**	255	65	0
71	109	0	0	**157**	135	148	0	**243**	189	255	255	**71**	0	103	255	**157**	22	255	0	**243**	255	60	0
72	112	0	0	**158**	135	150	0	**244**	192	255	255	**72**	0	108	255	**158**	27	255	0	**244**	255	55	0
73	115	0	0	**159**	135	155	0	**245**	199	255	255	**73**	0	113	255	**159**	32	255	0	**245**	255	50	0
74	117	0	0	**160**	135	157	0	**246**	204	255	255	**74**	0	118	255	**160**	37	255	0	**246**	255	45	0
75	122	0	0	**161**	135	160	0	**247**	210	255	255	**75**	0	123	255	**161**	42	255	0	**247**	255	40	0
76	126	0	0	**162**	135	163	0	**248**	215	255	255	**76**	0	128	255	**162**	47	255	0	**248**	255	35	0
77	128	0	0	**163**	135	166	0	**249**	220	255	255	**77**	0	133	255	**163**	51	255	0	**249**	255	30	0
78	131	0	0	**164**	135	170	0	**250**	225	255	255	**78**	0	138	255	**164**	56	255	0	**250**	255	25	0
79	135	0	0	**165**	135	174	0	**251**	232	255	255	**79**	0	143	255	**165**	61	255	0	**251**	255	20	0
80	135	0	0	**166**	135	177	0	**252**	236	255	255	**80**	0	148	255	**166**	66	255	0	**252**	255	15	0
81	135	1	0	**167**	135	180	0	**253**	240	255	255	**81**	0	153	255	**167**	71	255	0	**253**	255	10	0
82	135	2	0	**168**	135	184	0	**254**	248	255	255	**82**	0	158	255	**168**	76	255	0	**254**	255	5	0
83	135	3	0	**169**	135	188	0	**255**	255	255	255	**83**	0	163	255	**169**	81	255	0	**255**	255	0	0
84	135	4	0	**170**	135	192	0					**84**	0	168	255	**170**	86	255	0				
85	135	6	0	**171**	135	195	0					**85**	0	173	255	**171**	91	255	0				

Table 5: Color palettes for LOCS and RBS color maps.