# Classification of chroma reconstruction method by machine learning method

[1]Meng-Hsuan Kuo, [1]Yu-Chen Shen, and [2]Ting-Lan Lin
[1]Chung Yuan Christian University, Zhongli, Taiwan (ROC)
[2]National Taipei University of Technology, Taipei, Taiwan (ROC)

***Abstract*—In this paper, we propose a method to do the chroma reconstruction by using the machine learning for screen content images (SCIs). We create a feature matrix with twenty features in it, and use the classification learner to train the model. It's for predicting the subsample scheme. After the test, we get the experimental data. It shows us the correlation between the luma and chroma, and the accuracy of the model. Based on this situation, we find the accuracy of the model is not high enough, so we propose other methods in the paper to improve the accuracy of the model. After the improvement, it can make us get a more accurate predictable subsampling scheme, and we are able to make the chroma reconstruction better.**

## I. Introduction

Screen content images (SCIs) are computer generated images for screen display [1]. Because mobile phones have gained great popularity, SCIs have been widely used in many applications [2], [3]. When we deliver an image, the RGB image is first transformed into a YUV image, and the chroma UV will be subsampled by a subsampling scheme which the encoder uses. After subsampled, the image could be transmitted. Next, we use the subsampled image receiving from the decoder to predict the subsampling method and reconstruct the chroma image. The reason of luma-assisted chroma upsampling [4] is that it can improve the quality of the chroma image reconstruction [5]. In this paper, we use the machine learning to predict the subsampling scheme. We find an image, and we use a subsampling scheme named 4:2:0(A) to compress. Afterwards, we create a feature matrix which contains twenty features in it, using the classification learner and the feature matrix to train the model which is for predicting the subsampling method. We propose this method, as shown in Fig.1, to improve the accuracy of chroma reconstruction. Further, we are able to rebuild a better subsampled image.

## II. The Algorithm

### A. The Used Subsampling Scheme

There are many subsampling scheme, in this paper, we use a subsampling method called 4:2:0(A) to do the subsample. The 4:2:0(A) determines the one sampled U and V components, *U'* and *V'*, by averaging all the U and V components of the 2×2 UV block, as shown in Fig.2.

| | | | | |
|---|---|---|---|---|
| 132 | 138 | 134 | 129 | 134 |
| 135 | 142 | 137 | 133 | 138 |
| 133 | 139 | 135 | 129 | 135 |
| 129 | 135 | 130 | 126 | 131 |
| 131 | 138 | 133 | 129 | 133 |

| | | | | |
|---|---|---|---|---|
| 137 | | 133 | | 135 |
| | | | | |
| 134 | | 130 | | 132 |
| | | | | |
| 135 | | 131 | | 133 |

*Fig.2 An example used to illustrate the subsampled luma and chroma. (a)5x5 luma block. (b)Subsampled luma block by 4:2:0(A).*

### B. Relation Between the Subsampled Luma and Chroma

We propose a feature matrix to train the data for testing the method of chroma subsampling. Firstly, according to the subsampled chroma by 4:2:0(A), we subsample the luma by 4:2:0(A), and then place the values that equal to $\{(Y'_1-U'_1),(Y'_2-U'_2),(Y'_3-U'_3),\ldots,(Y'_n-U'_n)\}$ inside the first column in the feature matrix of method-all. The values that the subsampled luma by 4:2:0(L), 4:2:0(R), 4:2:0(DIRECT) and 4:2:0(MPEG-B) all minus the subsampled chroma-U by 4:2:0(A) are placed inside the second, third, forth and fifth column respectively. Secondly, based on the regular subsampled chroma-V by 4:2:0(A), we put the calculation of $\{(Y'_1-V'_1),(Y'_2-V'_2),(Y'_3-V'_3),\ldots,(Y'_n-V'_n)\}$ by each sub-sampling method into the next five columns of the same feature matrix.

### C. The Correlation Through the Linear Regression

In this subsection, we calculate the correlation between the

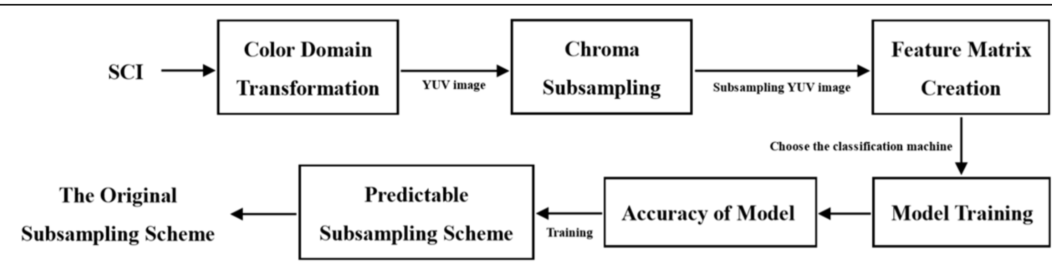


*Fig.1 The flow chart of predicting the subsample scheme*

subsampled chroma from the decoder and the estimated chroma, which is computed by the subsampled luma through the linear regression. The correlation for the block-pair ($U'^{(A)}$,Y') can be determined by the following system:

$$\begin{bmatrix} Y'1 & 1 \\ Y'2 & 1 \\ Y'3 & 1 \\ \vdots & \vdots \\ Y'9 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} U'1 \\ U'2 \\ U'3 \\ \vdots \\ U'9 \end{bmatrix}$$

Geometrically, the two correlation parameters, a and b, which can be solved by linear regression, could be the slope and intercept which can yield the sentence, U = aY + b. Therefore, we calculate the correlation by the subsampled chroma and the estimated value from each subsampling method, which can be expressed as ($aY' + b - U'^{(A)}$).

Accordingly, there are totally ten columns of the feature matrix placing the values which are, based on the subsampled chroma by the same method, the correlation by each subsampled luma, such as ($aY'^{(A)} + b - U'^{(A)}$), ($aY'^{(L)} + b - U'^{(A)}$), ($aY'^{(R)} + b - U'^{(A)}$), ($aY'^{(DIRECT)} + b - U'^{(A)}$), ($aY'^{(MPEG\text{-}B)} + b - U'^{(A)}$). By the same argument, we obtain the other five columns through the same subsampling scheme for chroma-V.

### *D. The Feature Matrix to Train the Data*

Since the feature matrix from the above is created, we add more pictures for gaining the higher accuracy. Firstly, we expand the feature matrix through calculating the feature values by the same theory from different pictures in turn. On the other hand, we can obtain the feature matrix with size, the number of pictures times 20.

## III. Experimental Section

In this section, we train the feature matrix by the embedded application, Classification Learner, to classify the values, which can be seen that the similar subsampling method should be put into the same range. Table 1 and Table 2 talk about the value of subsampled luma minus subsampled chroma U and V in five subsampling schemes respectively. As a result, based on the different classifiers, the highest accuracy score, 57.3%, is trained through the types of "Fine Tree," as shown in Fig.3, which means that there are 57.3% of values in the feature matrix can be classified to the clear range.

**Table 1 The Average Of Y Minus U Of Each Column**

| YU | Pic 1 | Pic 2 | Pic 3 | Pic 4 | Pic 5 |
|---|---|---|---|---|---|
| Subsampled Y(A) | 7.8303 | 18.4974 | 22.9362 | 24.2376 | 24.2103 |
| Subsampled Y(L) | 7.8474 | 18.5086 | 22.9382 | 24.2484 | 24.2162 |
| Subsampled Y(R) | 7.8467 | 18.5129 | 22.9362 | 24.2477 | 24.2160 |
| Subsampled Y(D) | 7.8585 | 18.5245 | 22.9408 | 24.2648 | 24.2279 |
| Subsampled Y(M) | 7.8344 | 18.4723 | 22.8267 | 24.1330 | 24.1128 |
| Linear Y(A) | 9.0454 | 18.4226 | 10.5015 | 18.0497 | 20.2781 |
| Linear Y(L) | 9.0607 | 18.4306 | 10.5032 | 18.0596 | 20.2885 |
| Linear Y(R) | 9.0604 | 18.4346 | 10.5032 | 18.0586 | 20.2897 |
| Linear Y(D) | 9.0707 | 18.4442 | 10.5043 | 18.0736 | 20.3080 |
| Linear Y(M) | 9.0393 | 18.3671 | 10.3921 | 18.9364 | 20.1853 |

**Table 2 The Average Of Y Minus V Of Each Column**

| YV | Pic 1 | Pic 2 | Pic 3 | Pic 4 | Pic 5 |
|---|---|---|---|---|---|
| Subsampled Y(A) | 9.0634 | 6.7409 | 12.1227 | 18.7779 | 7.5512 |
| Subsampled Y(L) | 9.0633 | 6.7408 | 12.1227 | 18.7680 | 7.5506 |
| Subsampled Y(R) | 9.0633 | 6.7408 | 12.1228 | 18.7684 | 7.5506 |
| Subsampled Y(D) | 9.0634 | 6.7409 | 12.1226 | 18.7777 | 7.5507 |
| Subsampled Y(M) | 9.0617 | 6.7400 | 12.1196 | 18.7519 | 7.5471 |
| Linear Y(A) | 3.5600 | 18.8892 | 4.0196 | 21.6875 | 15.1240 |
| Linear Y(L) | 3.5599 | 18.8890 | 4.0196 | 21.6827 | 15.1239 |
| Linear Y(R) | 3.5599 | 18.8891 | 4.0196 | 21.6828 | 15.1239 |
| Linear Y(D) | 3.5600 | 18.8893 | 4.0196 | 21.6895 | 15.1239 |
| Linear Y(M) | 3.5597 | 18.8878 | 4.0194 | 21.6733 | 15.1228 |

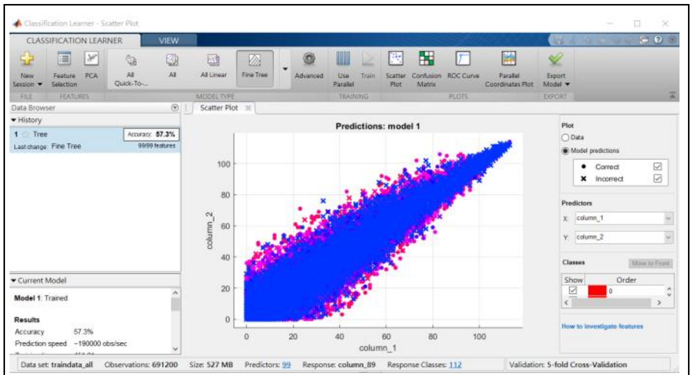

*Fig.3 The result of the training model.*

## IV. Conclusion

In this paper, we propose the method by machining learning which provides us with a predicted subsampling scheme that the encoder originally used. We obtain the result, the accuracy of the model, 57.3%, after the training. However, the accuracy is not high enough so that we will add more features and find the most suitable classification method in the future in order to improve the accuracy. Thus, we can predict the subsampling scheme for doing the chroma reconstruction more accurately and rebuild a better image.

## V. Reference


[1] K.-L. Chung, C.-C. Huang, and T.-C. Hsu, "Adaptive Chroma Subsampling-Binding and Luma-Guided Chroma Reconstruction Method for Screen Content Images," *IEEE Trans. Image Process.*, vol. 26, no. 12, pp. 6034-6038, Dec. 2017.

[2] W.-S. Kim et al., "Cross-component prediction in HEVC," *IEEE Trans. Circuits Syst. Video Technol.*, Nov. 2015. [Online].

[3] Y. Lu, S. Li, and H. Shen, "Virtualized screen: A third element for cloudmobile convergence," *IEEE Multimedia Mag.*, vol. 18, no. 2, pp. 4–11, Feb. 2011.

[4] J. Korhonen, "Improving image fidelity by luma-assisted chroma sub-sampling," in *Proc. IEEE Int. Conf. Multimedia Expo*, Jun./Jul. 2015, pp. 1-6.

[5] S. Wang, K. Gu, S. Ma, and W. Gao, "Joint chroma downsampling and upsampling for screen content image," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 26, no. 9, pp. 1595-1609, Sep. 2016.