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A novel camera colour characterisation model for the colour measurement of human skin

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Abstract

Accurate facial skin colour representation is highly required for an increasing number of applications, such as the solution of cosmetic products, the diagnosis of cutaneous diseases, and the manufacture of soft tissue prostheses. This study presents a novel camera colour characterisation model with higher predictive accuracy for the image-based colour measurement of human skin. More specifically, a digital imaging system was developed to collect the facial images of sixty human subjects from four ethnic groups. The newly collected human facial skin colour data and a conventional colour chart were selected as the training dataset, respectively, and three general techniques (linear transformation, polynomial regression, and root-polynomial regression) were utilised to derive the characterisation model by mapping camera digital signals to CIE XYZ tristimulus values. The predictive accuracy of each model was then verified using the mean CIELAB colour difference between actual skin colour measurements and the corresponding predictions from colour images. Results showed that the best model performance was achieved when the human skin colours of real subjects were used as the training samples and first order polynomial regression was used as the mapping algorithm.

Introduction

Conventionally, the colour of human skin is usually measured at fixed body locations using a contact-type spectrophotometer or a non-contact tele-spectroradiometer [1-2], and skin colour database have been developed by this measurement method to support multidisciplinary applications, e.g., in the cosmetic and dermatological industries [2,3]. With increasing interest in human skin colour, the variability of different types of measurement instrument, and the associated measurement parameters, including the pressures applied to the skin (or the measurement distance) and the size of measurement area, have been studied [4]. Although traditional colour measurement instruments have been widely used to collect skin colour data, they are inadequate for measuring colour over a wide area due to the limited instrument aperture size (usually 3 mm, 8 mm or 11 mm), especially when measuring colour on the human face where there is an uneven spatial distribution because of pigmentation and erythema [5].

Recently an imaging system that includes a digital camera, used as a two-dimensional colorimeter, was developed to conduct skin colour measurements [5-7]. This system captured an image of the human skin under controlled lighting conditions, and colorimetric values for each pixel in the image could be predicted using an appropriate camera colour characterisation method. Researchers have utilised this approach to obtain a large amount of skin colour information from captured images and then evaluated facial skin colour quantitively. For example, the effect of age on skin colour and colour heterogeneity in different ethnic groups was investigate by Rigal et al. from the recorded images of the whole face of the human subjects [8]. Kikuchi et al. developed a digital imaging system to evaluate aging effects and seasonal changes of facial skin colour distribution based on the collected facial images [7].

The key point of the image-based colour measurement is the model used to perform the camera colour characterisation, which transforms the RGB values of each pixel in the camera image, device dependent values, to appropriate device independent values, often CIE XYZ tristimulus values. Generally, the colour target-based approach is used for camera colour characterisation to determine the transformation model [9], using a suitable reference colour chart that contains a defined number of colour samples with known CIE XYZ tristimulus values, such as the Macbeth ColorChecker chart with 24 patches. The mathematical methods used to achieve characterisation mapping include linear transformation and polynomial regression [10]. Kikuchi et al. selected 100 colour chips from the Munsell Book of Color covering the skin colour area as training samples and derived a mapping matrix via linear least square regression [7]. Xiao et al. used a new silicon skin colour chart that included 90 colour samples and the polynomial regression for skin reflectance reconstruction [11].

Since the accuracy of skin colour prediction for the whole image is highly dependent on the characterisation model, it is desired to determine the appropriate training dataset and mapping method that are most feasible for human skin colour. In particular, conventional colour charts used for camera colour characterisation were originally developed for the graphic arts industry, and not specifically for skin colour measurement. And human skin presents as a non-flat, uneven surface (3D texture) and does not exhibit spatial uniformity over the measurement area (2D texture).

This study aimed to develop a camera colour characterisation model for skin colour measurement with the best prediction accuracy. First, a specific digital imaging system was developed to collect images of the human face. Second, different characterisation models were developed based on traditional and new training datasets and different mapping methods. Finally, the accuracy of each model was validated and compared in terms of the CIELAB colour differences between the measurements and the predictions for selected testing human skin colours.

Methodology

Digital imaging system for facial skin

A specific facial imaging system (Figure 1), that consisted of a Thouslite® LED lighting system and a high-resolution digital camera, was developed and used to collect facial images from human subjects. With the aim of quantitatively estimating the colour of facial skin, the light source in the digital imaging system

should be spatially uniform over the human face, and linear polarizers were used on the illuminators and the camera lens so as to eliminate glare and surface gloss caused by excessive reflection from the human face during image capture. Two LED cubes were used in this study to create the illumination with a Correlated Colour Temperature (CCT) of 6500 K. The actual CCT, colour rendering index (Ra), Duv and luminance were measured with a Konica Minolta CS-2000 tele-spectroradiometer and values of 6544 K, 95, 0.0064, and 127 cd/m^2 were obtained respectively. Figure 2 plots the relative spectral power distribution (SPD) of the 6500 K illumination used in the digital imaging system.

This digital imaging system was based on a Canon EOS 6D Mark II RGB DSLR digital camera that has a resolution of 6240 (width) × 4160 (height) pixels. For each measurement, the optimised camera parameters were ISO 640, aperture size f/5.6, and shutter speed 1/8 second. Since it was designed to collect Raw images without any post-processing, the white balance setting had no effect on camera Raw data in this study. To ensure the test site of the human face was positioned in a reproducible manner for image capture, a chin holder with a fixed height was placed in front of the camera at a distance of 120 cm. The human subject was required to keep his/her face clean without any makeup and have no bangs of hair in front of face. The Raw image of the human face was captured against a black background using the digital imaging system.

In this study, sixty human subjects (fifteen Caucasian, fifteen Chinese, fifteen Indonesian and fifteen Mexican - 22 males and 38 females in total) arranged to attend the facial image capture session. The age of the subjects ranged from 19 to 29 years. Before their participation, all the subjects were given an introduction to the study and a consent form that each was required to sign, according to the ethical review procedure from the University of Leeds.

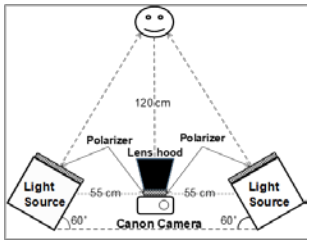

Figure 1 Digital imaging system.

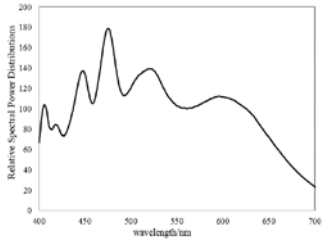

Figure 2 Relative SPD of the illumination.

Spectrophotometer measurement

The skin colour values of human face were measured at five facial locations (forehead, right cheekbone, left cheekbone, nose tip and chin centre) using a Konica Minolta CM-2600d spectrophotometer with SCI (specular component included) and SAV (3mm aperture). The measured spectral reflectance of each facial location was used to calculate the corresponding CIE XYZ tristimulus values, and associated CIELAB values, using the CIE 1931 standard colorimetric observer colour matching functions and the measured spectral power distribution of the nominally 6500 K illumination used during image capture. In this study, 300 facial skin colour data were collected from 60 human subject (60 human subjects × 5 facial locations).

Camera colour characterisation

The subset of facial skin colour data collected from sixty human subjects was treated as a training dataset for skin colour measurement and is referred to as the facial skin colour data (FSCD). In addition to the CIE XYZ tristimulus values measured at five facial locations on each human face, a similar measurement area, with a size of 50 × 50 pixels, was positioned in the each of the corresponding facial images and the average Raw RGB values of each location were derived using Dcraw and MATLAB software. In order to test the performance of conventional colour charts for predicting skin colour, the X-Rite Macbeth ColorChecker SG chart (CCSG) with 140 colour patches was also selected as a training dataset, given that there are 14 skin colour-related patches in this chart. Spectral reflectance of each training sample was measured using the spectrophotometer and then used to calculate CIE XYZ tristimulus values. In addition, an image of the colour chart was captured at the position as the human face using the digital imaging system set with the same camera parameters, just like the same approach for FSCD, and the average Raw RGB values of each sample were extracted using MATLAB. Hence, two training datasets were prepared for the development of camera colour characterisation model:

- CCSG: 140 colour patches of the Xrite ColorChecker SG chart,
- FSCD: A subset (200 out of 300) of the facial skin colour data collected in this study,

Additionally, three mathematical methods were tested to map camera Raw RGB values to CIE XYZ tristimulus values:

- Linear: linear transformation,
- PR: polynomial regression with three degrees,
- RPR: root-polynomial regression with two degrees [12].

The linear transformation converted Raw RGB values directly to CIE XYZ tristimulus values by a 3 × 3 matrix. The polynomial regression and root-polynomial regression with 1st, 2nd, and 3rd degree respectively were used to test characterisation mapping, where the Raw RGB variables were extended to different vectors. Table 1 lists the corresponding terms of the different mapping methods for camera colour characterisation. It should be noted that the first degree for PR and RPR has the same terms and was regarded as one algorithm [12].

Overall, six mapping methods including linear, 1st PR, 2nd PR, 3rd PR, 2nd RPR and 3rd RPR were adopted in this study to determine different characterisation models by the least-square fitting method, respectively based on two training datasets (FSCD and CCSG). Each model was then used to predict skin colour from the captured facial images by converting Raw image RGB values to CIE XYZ tristimulus values.

Table 1 The corresponding terms of different algorithms.

	terms
Linear	r, g, b
1st PR	$r, g, b, 1$
2nd PR	$r, g, b, r^2, g^2, b^2, rg, rb, gb, 1$
3rd PR	$r, g, b, r^2, g^2, b^2, rg, rb, gb,$ $r^2g, r^2b, g^2b, rg^2, rb^2, gb^2, r^3, g^3, b^3, 1$
2nd RPR	$r, g, b, \sqrt{rg}, \sqrt{rb}, \sqrt{gb}, 1$
3rd RPR	$r, g, b, \sqrt{rg}, \sqrt{rb}, \sqrt{gb},$ $\sqrt[3]{r^2g}, \sqrt[3]{r^2b}, \sqrt[3]{b^2g}, \sqrt[3]{rg^2}, \sqrt[3]{rb^2},, \sqrt[3]{gb^2}, \sqrt[3]{rgb}, 1$

Validation for predictive accuracy

Apart from the 200 facial skin colour data used as training dataset, the remaining 100 sets collected in this study were regarded as a testing dataset. The predictive accuracy of each

characterisation model was quantified by the average CIELAB colour-difference value between the measurements and the predictions of testing dataset [10]. The calculation formula is shown in Equation (1), where n is the number of samples in the testing dataset (n=100), i is the i^{th} testing sample, $L_0^*a_0^*b_0^*$ are the CIELAB values calculated from the measured skin colour on human face, and $L_1^*a_1^*b_1^*$ are the CIELAB values calculated from the CIE XYZ tristimulus values that were estimated from Raw image data by each characterisation model. Larger CIELAB colour-difference values represent lower predictive accuracy of the corresponding characterisation model.

$$\Delta E_{ab}^* = \frac{1}{n}\sum_{i=1}^{n} \sqrt[2]{(L_{0i}^* - L_{1i}^*)^2 + (a_{0i}^* - a_{1i}^*)^2 + (b_{0i}^* - b_{1i}^*)^2} \quad (1)$$

Results and discussions

The collected skin colour data from sixty human subjects, measured at five facial locations using a spectrophotometer, are illustrated in both the L^*C^* and a^*b^* plane, as shown in Figure 3, where the grey symbols mean the 200 facial skin colours used as training dataset and the orange ones indicate the remaining 100 facial skin colours used as testing dataset. It can be observed that the testing colours are uniformly distributed in the training colours. Since the facial skin colour data was collected from four ethnic groups including Caucasian, Chinese, Indonesian and Mexican, it may lead to the relatively large variation in the colour of the skin.

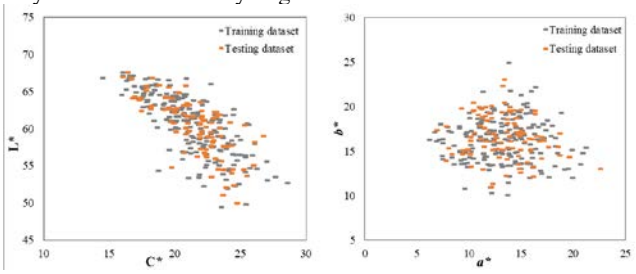

Figure 3 Distributions of training and testing colour in L^*C^* and a^*b^* plane.

Figure 4 was plotted to illustrate the relationship of skin colours between the spectrophotometer measurements and those corresponding values predicted from the same positions in the facial images, using different characterisation models. Figure 4(a) and (b) respectively show the predicted CIE $L^*a^*b^*$ values based on the FSCD and CCSG training datasets, where the x-axis represents the measurement results from the spectrophotometer and the y-axis indicates the prediction results using different mapping methods. The data on the 45° dash line indicates that the predicted value is the same as the measured value, and the farther the data is from the dash line, the larger the difference between the prediction and the measurement. It can be seen that the predicted values of the lightness attribute, L^*, are more similar to the measurement results than those of the redness, a^*, and yellowness, b^*. Moreover, the predictions with the FSCD training dataset, Figure 4(a), are more highly correlated with the measurements than those based on the CCSG colour chart, Figure 4(b).

To quantitatively compare the results predicted by different characterisation methods, the correlation coefficients of the CIELAB values between the spectrophotometer measurements and the predictions using each colour characterisation model are listed in Table 2. It can be seen that the results obtained by the FSCD training dataset generally have higher correlation with the measured CIELAB values, compared with the correlation coefficients calculated with CCSG colour chart. From the results of different mapping methods, it is indicated that 1st polynomial regression has higher correlation coefficients than other methods when using FSCD as a training dataset, which is different from the finding in the Li et al. study where the higher order polynomial model performed better than that with a lower one [10]. That may be because the training dataset and testing dataset comprised the skin colour collected from real human faces as opposed to the more usual colour chart with uniform, untextured, colour patches.

Table 2 The correlation coefficients of CIELAB values between the measurements and the predictions by different models.

	Model	Linear	1st PR	2nd PR	3rd PR	2nd RPR	3rd RPR
L^*	FSCD	0.89	0.90	0.88	0.88	0.88	0.88
	CCSG	0.85	0.84	0.84	0.85	0.84	0.84
a^*	FSCD	0.56	0.83	0.77	0.77	0.82	0.83
	CCSG	0.46	0.74	0.76	0.76	0.75	0.76
b^*	FSCD	0.76	0.78	0.70	0.74	0.61	0.68
	CCSG	0.52	0.74	0.77	0.76	0.76	0.77

In addition, the correlation coefficients calculated using CIELAB values (Table 2) are not as high as the results in the study by Kikuchi et al. [7], possibly because the skin colour data in our study was collected from five facial locations of sixty human participants from four ethnic groups, and again, this represents relatively large colour variation. In contrast, Kikuchi et al. only recruited Japanese women for the collection of skin colour, and the correlation coefficients were calculated for individual facial areas.

In order to evaluate the performance of different characterisation methods on skin colour estimation, the average, maximum, minimum and standard deviation of the CIELAB colour-difference values, between the spectrophotometer measurements and the predictions, using each model were calculated and are listed in Table 3 and Table 4, respectively based on FSCD and CCSG as the training dataset. Figure 5 summarises the averaged colour differences calculated with twelve characterisation models which were developed from two training datasets and six mapping methods.

Table 4 The predicted CIELAB colour differences using different mapping methods with CCSG as training dataset.

CCSG	Linear	1st PR	2nd PR	3rd PR	2nd RPR	3rd RPR
Mean	3.98	3.48	3.56	3.51	3.54	3.47
Max	8.50	7.69	8.07	7.74	8.19	7.76
Min	0.80	0.88	1.00	0.76	1.25	0.77
SD	1.62	1.52	1.61	1.59	1.56	1.54

Table 3 The predicted CIELAB colour-differences using different mapping methods with FSCD as the training dataset.

FSCD	Linear	1st PR	2nd PR	3rd PR	2nd RPR	3rd RPR
Mean	3.08	2.47	2.65	2.70	2.55	2.53
Max	7.78	5.75	8.21	7.75	6.46	6.32
Min	0.95	0.19	0.45	0.55	0.32	0.33
SD	1.26	1.12	1.33	1.33	1.25	1.21

(a) FSCD as training

(b) CCSG as training

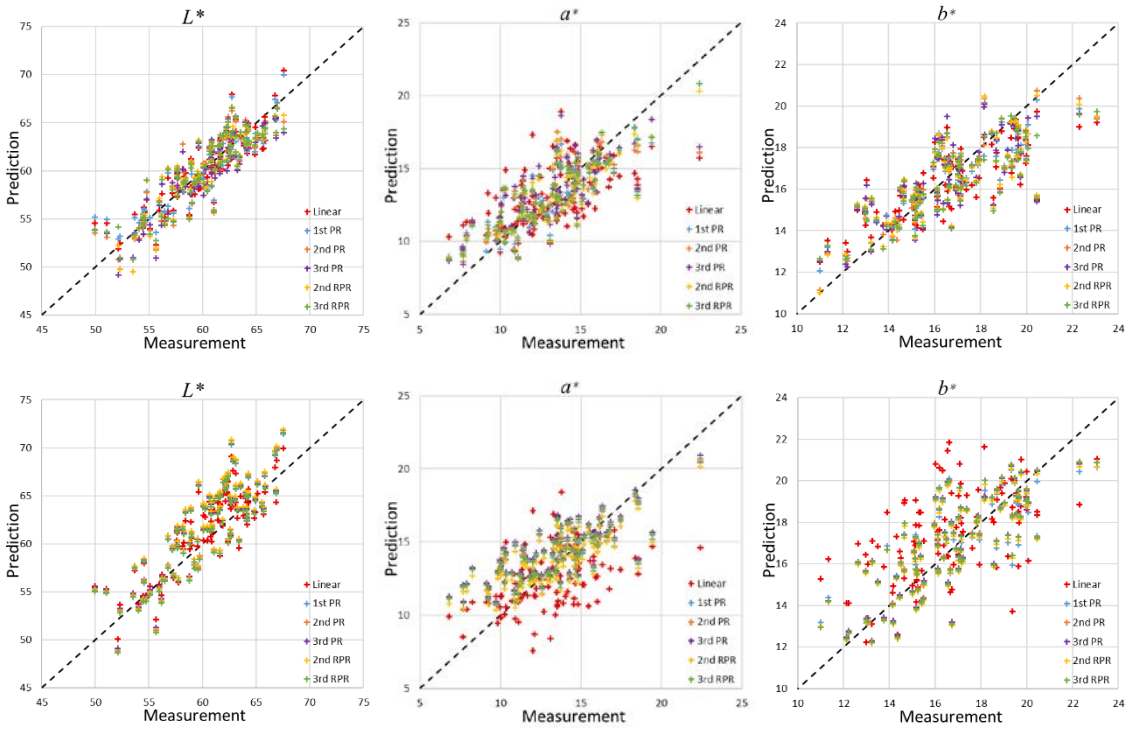

Figure 4 Comparison of CIELAB values from spectrophotometer measurements and those predicted from digital camera data by different methods: (a) comparison data based on FSCD as training dataset, (b) comparison data with CCSG as training dataset.

The results in Table 3 show that when FSCD was treated as the training dataset, the 1st polynomial regression achieves higher predictive accuracy than other algorithms, with the smallest mean CIELAB colour-difference value of 2.47 ΔE^*_{ab} , and the corresponding maximum, minimum and standard deviation are also the smallest results. On the contrary, the largest mean colour difference was obtained from the linear transformation, with the value of 3.08 ΔE^*_{ab}, and it also had the largest values of maximum, minimum and standard deviation. Additionally, the results for 2nd and 3rd root-polynomial regression have slightly smaller predictive error than those for 2nd and 3rd order polynomial regression. That is possibly because the skin colour is non-uniform and the mapping method with more complex extensions is not realistic for skin colour, considering the root-polynomial regression is a degree-root (low complexity) result of polynomial regression which has less extended terms (as shown in Table 1).

When the CCSG colour chart was utilised as the training dataset, the obtained mean CIELAB colour-difference values calculated with six mapping algorithms were all larger than 3.47 ΔE^*_{ab} (as shown in Table 4) which is a larger predictive error in skin colour measurement. Furthermore, the model determined by the linear transformation has the lowest predictive accuracy with the largest average and maximum of CIELAB colour-difference values.

From the histogram of the mean CIELAB colour-difference values, it can be clearly seen that selecting FSCD as the training dataset yields smaller CIELAB colour-difference values than the CCSG dataset, which indicates that the real facial skin colour data is preferred for skin colour estimation as opposed to the conventional colour chart. Moreover, the smallest predictive colour-difference value was achieved when the FSCD dataset was selected as the training dataset and 1st order polynomial regression was used as the mapping method. Thus, that is the model with the highest predictive accuracy, and it is recommended for skin colour measurement. In a future study, further investigation will be carried out to assess this model from the performance in different practical applications.

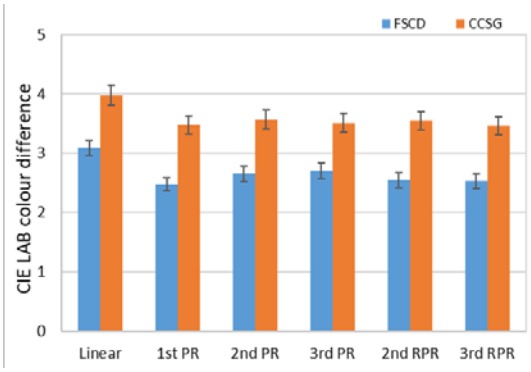

Figure 5 The averaged CIELAB colour difference calculated by each model.

Conclusions

In this study, a digital imaging system for capturing images of facial skin was developed, and different methods of camera colour characterisation were applied for skin colour measurement, based on the collected facial images from sixty human subjects from four ethnic groups. Two training datasets and six mapping algorithms were investigated to generate different characterisation models that transform camera Raw RGB values to CIE XYZ tristimulus values.

The results showed that using the new real facial skin colour data as the training dataset performed better than using the conventional colour chart (Macbeth ColorChecker SG), with higher correlation coefficients and smaller CIELAB colour differences. Moreover, it was found that 1st polynomial regression, from six algorithms tested, achieved lower prediction error of facial skin colour.

Thus, a novel camera colour characterisation model with higher predictive accuracy was developed for the image-based colour measurement of human skin, using the collected facial skin colour data as the training dataset and first-order polynomial regression as mapping method. Our investigation of different methods of camera colour characterisation on skin colour estimation complements previous research on image measurement for skin colour.

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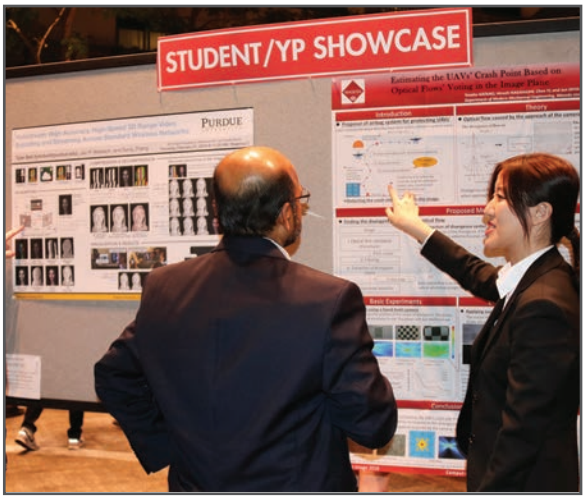

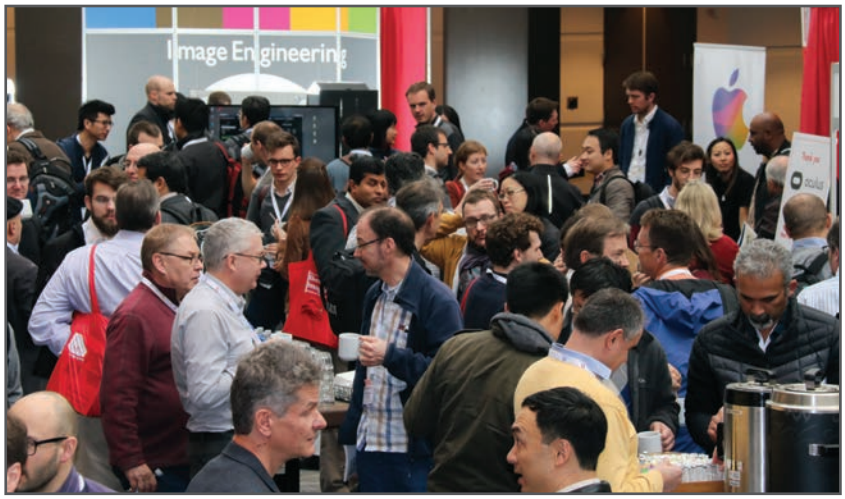

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