2011 12th International Conference on Computer-Aided Design and Computer Graphics

Color-Mood-Aware Clothing Re-texturing

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Abstract

In this paper,we present a novel color-mood-aware technique to re-texture clothing in a photograph.An efficient classification algorithm is developed to classify clothing textures using color mood scheme. To re-texture the clothing, our approach first computes the gradient maps for the cloth region to be replaced and then calculates the texture distortion coordinates on the projected cloth region according to the gradient maps. After the user selects a target clothing texture from the classified clothing texture database, the lighting and shading effects on the original photograph is transferred using the HSV color space. Experimental results show that the proposed approach successfully re-textures the clothes in photographs while preserving the geometry and lighting features.

1. Introduction

Clothing re-texturing is a process to replace the existing clothing texture in the concerned region of a photograph by new materials while preserving the original shading and lighting effects for e-entertainment multimedia applications. Although there exists a rich body of work on image texturing and re-texturing [2], [3], [6], [7], [8], the clothing re-texturing receives relatively little attention.

Given a single photograph capturing a person wearing a piece of cloth (e.g. a skirt or a t-shirt), we want to allow users to simulate the person's looking and mood when dressed in clothes of different textures through some texture replacing techniques. For this purpose, we develop a new texture classification algorithm based on color mood scheme [1]. We also developed an improved texture replacement algorithm for replacing the original clothing texture with a correctly deformed and shaded texture of personalized mood. Our approach requires no 3D models, and can generate the highly realistic final results.

It has been a long history for the research on relationships between colors and their evoked moods. Whelan *et al.* [1] developed a color mood scheme, which defines the 24 mood categories and their primary corresponding colors. However, the current approaches [1] does not address the problem on how to calculate which color mood it belongs to when given a single clothing texture. In our paper, we developed such a novel classification method for clothing textures using the histogram-based color mood scheme. Figure 1 shows the clothing re-texturing results with our approach using the Trendy mood (Figure 1(b)), Traditional mood (Figure 1(c)), and Earthy mood (Figure 1(d)), respectively.

2. Clothing texture classification

2.1. Color mood scheme

In order to create an efficient mood table to guide the clothing texture classification, we adopt the primary color based histogram to denote the color mood [9]. Figure 2 shows the 24 mood categories and their primary corresponding colors. The employed color mood scheme [1] encompasses a broad range of color moods and is thus suitable for texture classification. For instance, the Tropical mood (Figure 3c2) often expresses traditional themes such as richness and stability, which is frequently seen in the decor of banks and legal offices, suggesting permanence and value. The Vital mood (Figure 3c3) usually expresses a feeling of vigor and warmth, it is youthful and playful and is often seen in advertisements displaying energetic lifestyles and personalities. The Dependable mood (Figure 3a1) is interpreted as dependable and reliable, communicating firmness and strength. We refer readers to Whelan's book [1] for more information on color moods and their emotions.

2.2. Color mood guided classification

For the purpose of easy clothing re-texturing, we develop an efficient clothing texture classification algorithm based on the color mood. In order to classify the input textures into one of the 24 color moods, we employ the mood histogram to determine which mood it belongs to. Our color mood histogram is defined as $h(c_k) = n_k, k \in [0, 23]$. Here c_k is the kth color mood in the mood interval $[c_0 =$Powerful mood, $c_1 =$Rich mood, ..., $c_{23}=$ Professional mood$]$ and n_k

978-0-7695-4497-7/11 $26.00 © 2011 IEEE
DOI 10.1109/CAD/Graphics.2011.9

(a) input (b) Trendy mood

(c) Traditional mood (d) Earthy mood

Figure 1. Clothing re-texturing using color mood scheme: (a) the input photograph (the re-texturing cloth region (with red boundary)); (b)-(d) the re-texturing results. Note that the input clothing textures are the insets in (b)-(d) (left bottom).

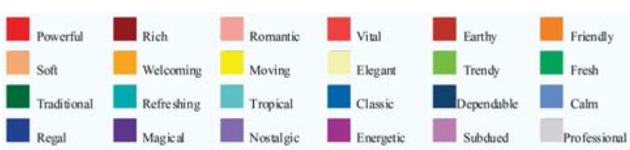
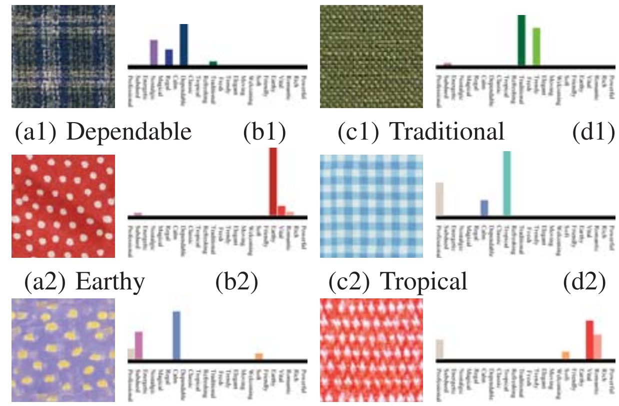


Figure 2. The 24 color moods and their corresponding primary colors [1].

is the number of pixels in the clothing texture whose color mood is c_k. In our application, the color mood histogram is calculated for each sample clothing texture in the database. Each pixel of the clothing texture is compared with all 24 moods to find the closest mood, then the pixel is added to that color mood's bin c_k in the color histogram $h(c_k)$. Here, the Euclidean distance metric is employed for measuring the closest mood in our scheme.

In order to classify a clothing texture into some corresponding color mood, we determine its category by locating the mood with the highest frequency in its histogram. A similar color mood histogram scheme is used in [9] for



(a1) Dependable (b1) (c1) Traditional (d1)

(a2) Earthy (b2) (c2) Tropical (d2)

(a3) Calm (b3) (c3) Vital (d3)

Figure 3. Classified color moods and their corresponding mood-histograms: (a1)-(a3),(c1)-(c3), the input textures; (b1)-(b3), (d1)-(d3), the mood-histograms.

classified sub-database (Soft mood)

classified sub-database (Calm mood)

Figure 4. Classified clothing texture database using color mood scheme.

color transfer between images. Figure 4 shows some results classified by the color mood histogram approach in our clothing texture database.

3. Clothing re-texturing approach

The color mood guided clothing re-texturing approach consists of five steps, which are outlined as follows:

1) Calculate the gradient map: $\nabla I_G(x,y) = (I_L(x{+}1,y) - I_L(x{-}1,y))/2, (I_L(x,y{+}1) - I_L(x,y{-}1))/2$. Here, I_L is the luminance image of the input photograph with the replaced region Ω.
2) Smooth the gradient map $\nabla I_G(x,y)$ by applying the bilateral filter, and get the filtered gradient map $\nabla I^s_G(x,y)$.
3) Compute the texture indices $[t_x, t_y]$ according to the sm-oothed gradient map $\nabla I^s_G(x,y)$.
4) Derive the new color $I'(x,y)$ from its original color and the input color mood clothing texture $T_G(t_x,t_y)$.

5) Transfer the lighting and shading effect from the original photograph in the HSV color space.

Our approach focuses on computing a locally-consistent gradient maps, and then we use these gradients to derive the texture distortion for the re-texturing region. When an input photograph I is given, we first computes the gradient field $\nabla I_G(x, y)$ in terms of neighboring luminance values of its luminance image I_L:

$$\nabla I_G(x, y) = ((I_d(x+1, y) - I_d(x-1, y))/2, \\ (I_d(x, y+1) - I_d(x, y-1))/2) \quad (1)$$

we use the gradient bilateral filter (GBF) to smooth the gradient map $\nabla I_G^s(x, y)$. Here, the gradient bilateral filter at pixel p is defined by

$$\nabla I_G^s(x, y) = GBF(\nabla I_G(x, y)) \\ = \frac{1}{K} \sum_{q \in \nabla I_G} G\sigma_s(\|p - q\|) G\sigma_r(\|\nabla I_G^p - \nabla I_G^q\|) \nabla I_G^p$$

$$K = \sum_{q \in \nabla I_G} G\sigma_s(\|p - q\|) G\sigma_r(\|\nabla I_G^p - \nabla I_G^q\|) \quad (2)$$

where σ_s controls the spatial neighborhood, σ_r controls the influence of the intensity difference, $G\sigma_r(\cdot)$ and $G\sigma_s(\cdot)$ are the kernels in the form of the Gaussian function.

3.1. Mood-aware clothing re-texturing

In general, the recovered gradient field is sufficient to be used to estimate a warping of a color-mood-aware clothing material texture T. Our approach employs the lazy snapping technique [4] to segment the cloth region. Unlike [8], our algorithm does not need to generate a proper triangle mesh for calculating the texture distortion coordinates. For extra flexibility, the smoothed gradient map is introduced to calculate the texture indices $[t_x, t_y]$ by

$$\nabla t_x = (1 + k_1) * \nabla_x I_G^s, \nabla t_y = (1 + k_2) * \nabla_y I_G^s \quad (3)$$

$$\Delta t_x(x, y) = div \nabla t_x(x, y), \Delta t_y(x, y) = div \nabla t_y(x, y) \quad (4)$$

where k_1 and k_2 are the scale parameters, Δ and div represent the Laplacian and divergence operator, respectively. We adopt the Poisson equation to solve them and it runs very fast [5]. In order to further reduce the computational cost, a down-sampling version of the gradient map is used to solve the Poisson equation.

The new color value $I'(x, y)$ is derived from its original color and the color of the mood-aware clothing texture $T(t_x, t_y)$ with the following matting equation

$$I'(x, y) = (1 - f) * T(t_x(x, y), t_y(x, y)) + f * I(x, y) \quad (5)$$

where f is a scalar parameter that linearly interpolates the original cloth color, and the replaced clothing texture color

(a) input (b) Dependable mood

(c) Rich mood (d) Calm mood

Figure 5. Results by our algorithm: (a) the input photograph; (b)-(d) the re-texturing results.

which is interactively selected from the classified clothing texture database by the user.

Due to the lack of simulating the lighting and shading effects exhibited in the cloth region, the replaced result looks flattening if we only use the texture distortion coordinates deduced by the above Poisson equation. In order to make the realistic appearance of the replaced clothing region, the lighting and shading effects must be transferred properly. The final relighting result $I''(x, y)$ can be obtained by copying the H, S components of the replaced clothing texture to the target photograph in the cloth region, and adopting a weighted blending of the V component of both the replaced clothing texture and the original photograph:

$$I''_H(x, y) = I'_H(x, y), I''_S(x, y) = I'_S(x, y), \quad (6)$$

$$I''_V(x, y) = (1 - k_3) * I'_V(x, y) + k_3 * I_V(x, y) \quad (7)$$

where $I'_H(x, y)$ and $I'_S(x, y)$ are the corresponding chrominance channels of the replaced clothing texture. $I'_V(x, y)$ and $I_V(x, y)$ are the intensity channels of the replaced cloth

(a) input (b) Subdued (c) Calm (d) Trendy (e) Elegant (f) Calm

Figure 6. Experimental results by our approach: (a) the input photograph (the re-clothing region (with red boundary)); (b)-(e) the re-texturing results using the Subdued mood, Calm mood, Trendy mood, Elegant mood, and Calm mood, respectively.

texture, the original photograph, respectively. k_3 defines the balancing weight between the replaced clothing texture and the brightness of the cloth region on the original photograph.

4. Experimental results

We have applied our proposed algorithm to a variety of photographs and the experimental results demonstrated that our clothing re-texturing technique can generate visually pleasing results. Figure 6 shows some experimental results of our clothing re-texturing algorithm. The example shows, in order from left to right, the input photograph, the replacement result by Dependable mood (Figure 6(b)), Rich mood (Figure 6(c)), Calm mood (Figure 6(d)), and Regal mood (Figure 6(e)), respectively. Figure 1 shows more re-texturing results using the textile material textures.

As shown in Figure 1 and Figure 5, the cloth ripples and wrinkles are faithfully transferred in the final clothing replacement results. Additionally, our approach produces similar shadow and illumination effects on the cloth region as that of the input photograph. Moreover, we can combine our method with other augmented applications, such as the virtual fashion show and the augmented reality system on cloth with realistic illumination.

5. Conclusion and discussions

We have presented a novel color-mood-aware clothing re-texturing algorithm for multimedia applications. Our approach computes the gradient maps for the region to be replaced, calculates the texture distortion coordinates on the projected region of the underlying surface according to the gradient maps. The lighting and shading effect on the original photograph is transferred using the HSV color space. Given a set of clothing material, we calculate the color mood histogram for each texture, and build a database of clothing textures classified by color mood. Thus, the user can easily select the target clothing texture of preferred mood from the classified clothing texture database. Our system is better suited for the virtual cloth show and simulation application in the entertainment industry, where the user can easily simulate the visual effect of different cloth.

6. Acknowledgements

This work is supported by the NSFC (Grant No. 60903068), the Key Program of NSFC-Guangdong Union Foundation (Grant No. U1035004), and Excellent Young Teacher Research Fund of Beijing Institute of Technology (2009Y0707). The Project-sponsored by SRF for ROCS, SEM. Yanwen Guo was supported by the NSFC (Grant No. 61073098).

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