

Towards Realism in Facial Image Transformation: Results of a Wavelet MRF Method

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Abstract

The ability to transform facial images between groups (e.g. from young to old, or from male to female) has applications in psychological research, police investigations, medicine and entertainment. Current techniques suffer either from a lack of realism due to unrealistic or inappropriate textures in the output images, or a lack of statistical validity, e.g. by using only a single example image for training. This paper describes a new method for improving the realism and effectiveness of facial transformations (e.g. ageing, feminising etc.) of individuals. The method aims to transform low resolution image data using the mean differences between the two groups, but converges on more specific texture features at the finer resolutions. We separate high and low resolution information by transforming the image into a wavelet domain. At each point we calculate a mapping from the original set to the target set based on the probability distributions of the input and output wavelet values. These distributions are estimated from the example images, using the assumption that the distribution depends on the values in a local neighbourhood of the point (the Markov Random Field (MRF) assumption). We use a causal neighbourhood that spans multiple coarser scales of the wavelet pyramid. The distributions are estimated by smoothing the histogram of example values. By increasing the smoothing of the histograms at coarser resolutions we are able to maintain perceived identity across the transforms while producing realistic fine-scale textures. We use perceptual testing to validate the new method, and the results show that it can produce more accurate shifts in perceived age and an increase in realism.

Categories and Subject Descriptors (according to ACM CCS): I.4.7 [Image Processing and Computer Vision] Feature Measurement (Texture), I.3.8 [Computer Graphics] Applications.

1. Introduction

The ability to alter perceived attributes of a facial image, such as age, race or sex has found application in psychological research for producing controlled experimental stimuli. Other application areas include the ageing of photographs of wanted or missing persons, predicting the outcome of medical intervention (e.g. for skin conditions) and modifying the appearance of actors in the film industry. Previous methods based on group differences have suffered because of a lack of texture in facial blends used to define the transform. Methods to compensate for this, by modifying the amplitude of multi-scale edges (via wavelets), have produced some improvements, but the resulting images still lack realism. They also fail to sufficiently alter the perceived age when rejuvenating and the perceived sex when transforming from male to female. More recent methods based on single images have produced some more realistic results, but do not necessarily define the typical or most likely alterations to a given face, i.e. they could be biased by the choice of example.

In this paper we propose a new method based on locally estimated probability distributions. These distributions are conditional on the points in a neighbourhood of the point being synthesised. The estimated conditional distributions for the original and output pixel defines a mapping from original to the new value. Performing the estimation in the wavelet domain offers several advantages over spatial domain processing. It is inherently multi-scale, improving the reconstruction

quality for the same size neighbourhood. The low and high resolution information is cleanly separated, so that processing at high resolutions does not overwrite lower resolution information. For this application it also has the advantage that we can alter the transformation parameters with scale, so that we retain the low resolution information (which codes mainly for face shape) but can select more specific textures (e.g. wrinkles and stubble) at higher resolutions.

In the remainder of this paper we first review the relevant literature in texture synthesis, image-fusion, facial image prototyping and facial image transformation. We then describe the new method in detail, followed by visual transformation examples for facial ageing and gender change. Finally, we present the results of a perceptual study that demonstrates that the new technique can accurately age and rejuvenate faces to the age of the target group, and offer a significant increase in perceived realism.

2. Literature Review

2.1 Texture synthesis by analysis

The main problem in previous facial transformation methods has been identified as the lack of appropriate transformation of the facial textures. Synthesising patches of texture from examples has been the focus of a considerable number of research papers. The statistical nature of textures inspired methods that used global

properties of the images, such as the image histogram and the histograms of wavelet subbands [HB95]. Starting with random noise, the image and subband histograms are alternately matched to the target histograms in an iterative process. This method produced excellent synthetic results for random textures, but was not able to reproduce more structured textures, such as hair. Extensions to the method using additional measures of the wavelet histograms (such as correlations within and across subbands) improved the results, but still failed on more complex textures [SP98].

An alternative to global optimisation of texture parameters is to look at local features. In MRF-based texture synthesis [JUL62] [HS81] [CC85a] [CC85b] [CJ83] it is assumed that the probability distribution of a pixel's intensity is dependent on its neighbours. The aim is to construct a texture such that the local conditional probability distribution functions of the synthesised image match those of the original texture sample. The original MRF methods proved to be very slow due to the need to rebuild the histograms or select suitable matching neighbourhoods at each pixel by scanning the entire image. Several methods that approximate the full MRF method have been devised, usually by searching the example image for the best matching n pixels, and choosing one of these using stochastic sampling [EL99]. Speed optimisations include using a multiscale approach [PL98] (i.e. building up a low resolution approximation to the texture and then refining it to higher resolutions) and fast search algorithms [WL00]. Performing the texture synthesis in the wavelet domain has allowed proper separation of information at different spatial scales [ZWT98], including the very efficient approximation using a neighbourhood consisting of only lower resolution subbands [DEB97].

2.2 Facial Image Prototyping Literature

Several of the proposed facial transformation methods start by constructing a prototype of the source and target sets. The creation of prototype images has a long history dating back to the methods of Francis Galton who created photographic averages by using multiple exposures after aligning the eyes and mouth [GAL78]. More recently, prototypes have been created by digitally blending faces together, after normalising the shape to the average using image warping [BP93]. Simple averaging of the spatially aligned images does not produce representative textures and several improvements have been suggested. Wavelet-magnitude based texture prototyping [TBP01] uses the smoothed magnitude of the wavelets as a measure of the average local activity in different spatial locations, orientations and scales across the set. The wavelet values of the simple average are locally rescaled to approximate these activity levels. An alternative wavelet histogram method has been proposed in which the histograms of the prototype image and its wavelet subbands are modified to match the (mean) histograms of the image set [MCV04]. These two methods produce visually similar results, with random textures

being well represented, but more structured textures (such as the hair) still appearing rather unrealistic and unrepresentative of the set.

An alternative approach is to use a local neighbourhood surrounding each point to estimate the most likely pixel value for the prototype [TID04]. By comparing the values in the neighbourhood with the matching neighbourhoods in the training set a probability distribution can be estimated. The highest probability value is selected from this distribution, then this pixel forms part of the neighbourhood for succeeding pixels. A causal neighbourhood, spanning two neighbouring scales, was used for efficiency and reconstruction stability. The probability distributions were estimated by smoothing the histograms of neighbourhood values. Certain choices of smoothing parameters caused locking of the algorithm onto large parts of a single image in the training set. To avoid this behaviour the histogram smoothing was increased at lower spatial scales, to give a more average global appearance, but leaving more specific (and therefore realistic) fine scale textures. Although no perceptual study was conducted, the results appear very realistic, although there is a problem of occasional discontinuities in the reconstructed images. These discontinuities are probably caused by the overlap in information content between neighbouring scales in a multiresolution (Gaussian) pyramid. To improve on this, a wavelet domain version of the algorithm has been proposed [TID05], with an improvement in realism.

2.3 Image Fusion Literature

Image prototyping is a specialised example of multiple image fusion. The more usual problem is that of fusing multiple images of the same scene, taken using several different sensors (e.g. visible and infra-red) or taken under different conditions (e.g. focused on different objects or with different exposures). Methods based on wavelet pyramids have proved successful, with various algorithms for combining the individual wavelet components proposed. Point-based methods include selecting the wavelet coefficient with the largest absolute value or making a simple average. Other methods inspect the values in a window about each point when calculating the value. These methods include choosing the pixel from the image with the largest absolute value in the window [LMM95]), making an average of the matching points that is weighted by the local activity levels in the window [BK93] or weighting the samples based on the contrast sensitivity of the human visual system [WRM95]. Several comparisons of wavelet-based image fusion schemes have been conducted [ZB99] [BB04] [HCB02] and these indicate that over-complete wavelet decompositions are preferable to critically sampled decompositions (for reconstruction stability and fewer artefacts), that region-based methods give improved results over point-based methods and shorter filters reduce the number of artefacts in the resulting fused images.

2.4 Facial Transformation Literature

Early facial transformation methods used prototypes to define the shape and colour differences between two groups (e.g. young and old). These differences are then added to an individual to shift their appearance between the groups in a two stage process [RP95]. First, the differences between the outline shapes of the two prototypes is added to the subject's shape after suitable rigid body registration. Then the colours are altered by warping the two prototypes and the subject's image into the new shape and adding the colour difference to the subject at each pixel. The lack of texture processing is particularly evident when reducing the age of older faces (because the wrinkles are still present in the output) and when feminising male faces (because of the presence of stubble etc. in the output). Perceptual tests have shown that the reduction in perceived age is statistically insignificant when attempting to shift the perceived age from 55 to 35 years old in Caucasian adults [TBP01].

The wavelet-magnitude prototyping method described above was extended to facial transformation, by rescaling the magnitude of the wavelet values in the transformed image to match those of the target prototype [TBP01]. The method suffers from the same problems with unrealistic structured textures as the wavelet-magnitude prototyping method. In addition, it is not really a transform, in the sense that the smoothed wavelet magnitude functions of the final image are *copied* from the prototype, rather than being *shifted* by the difference between the source and target prototypes. Even so the perceived age shift was much improved, although still falling short of the desired age shift, by 50%, when reducing the perceived age.

An alternative approach is to perform the ageing in a principal component space. Lanitis et al [LTC02] learn ageing paths through a PCA based face-space from example images of the same individuals at different ages, using the assumption that the kind of ageing to apply is dependent on appearance. PCA faces often suffer from problems with unrealistic textures due to the blurring of textural features, particularly near to the mean.

Several authors have developed heuristic techniques based on the information in a single image. Bastanfard et al [BBT*04] combined shape changes based on anthropomorphic measurements with wrinkle “in-painting”, in which pixels defined in a binary mask are smoothed by a local diffusion process. In a similar approach, Mukaida et al [MAK*02] [MA04] automatically segment the spots and wrinkles using blob analysis. These features can then be amplified to give the appearance of ageing or age reduction. These techniques have the advantage of speed, but make the assumption that the de-wrinkled skin is blurred, rather than having some structure (e.g. pores, fine lines, freckles). It is also not clear how wrinkles or spots are added to a face if there is no underlying wrinkle to (de) exaggerate. Gandhi [GAN04] models wrinkles using image-based surface detail transfer, which copies the high-frequency components (corresponding mainly to

wrinkles) between two images. The use of a single example may introduce an ageing or age reduction that is not representative of either the typical or most likely change that an individual will experience. Also some larger wrinkles may have components at lower frequencies that are not copied.

Three dimensional models of ageing and wrinkles have also been explored for use in building and animating virtual humans [BKT*00] [LM99] [WM95] [WMM99]. These use a collection of generic ageing masks and 3D models of skin and wrinkles based on a multi-layer tissue model to perform simulated ageing and allow animation. Blanz et al [BV99] have used 3 dimensional PCA face models and have demonstrated expression alterations. These expression transforms can be applied to a 2D image by estimating the best 3D face model and lighting parameters by a minimisation technique. The technique described here could be combined with these 3D methods, improving the transformation of the 3D texture-map with more appropriate skin texture changes.

3. Method

The method proposed in this paper extends the wavelet-based MRF methods for facial prototyping described in [TID05] to transforming between two groups. To transform a face image between two groups we start by performing the shape and colour changes using the technique of [RP95] (Figure 1). We add the average shape difference between the two groups to the subject's feature points. The subject and all the images in both groups are warped into this new shape. The 2 colour channels (e.g. the U and V channels in a YUV colour space) are altered by adding the average difference between the colours in the two groups to the colours of the subject's face.

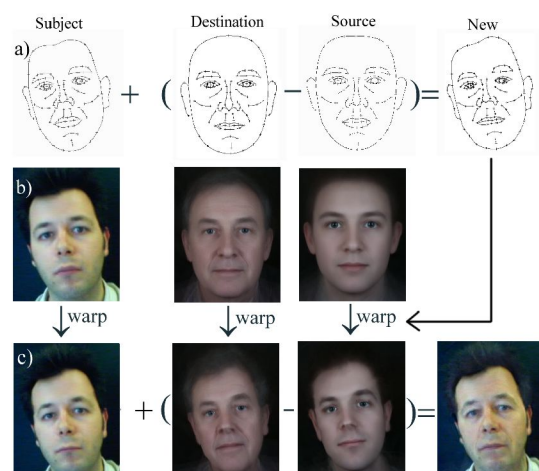


Figure 1 The previous transformation process. (a) The new face shape is calculated by adding the average shape difference. (b) The subject and average images are warped into the new shape. (c) The average colour difference is added to each pixel.

Next we transform all the images' intensity components (Y channel) into a wavelet basis. In this work, we use a redundant (i.e. over-complete) image decomposition, which builds a pyramid of horizontally and vertically filtered versions of the image at different resolutions. The filters we use approximate a first derivative of the image, and we use an exact reconstruction algorithm when performing the final image synthesis. The use of an over-complete basis with short filters has been shown to improve reconstruction stability in image fusion [BB04]. As with the filters used in [TBP01], we can perform an exact reconstruction by up-sampling, filtering and addition. The down and up-sampling of the low-pass filtered image requires that the high-pass components are convolved with different filters at odd and even pixels. Figure 2 shows the analysis and synthesis process and Table 1 gives the corresponding filter coefficients.

The MRF algorithm is then applied to these pyramids. First, the low-pass residual is transformed by adding the difference between the average low-pass residuals of the two groups to the subject. The algorithm then proceeds from low to high resolution subbands, scanning across each and choosing wavelet coefficients that match the (cumulative) probability of the input values.

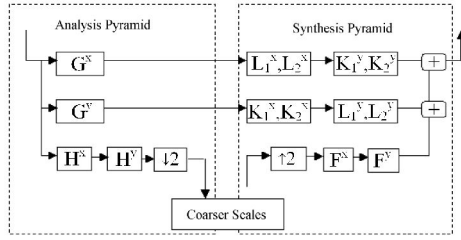


Figure 2 The construction of one level of the wavelet pyramid. A pair of filters in a box indicates application to even and odd pixels respectively.

	-2	-1	0	1	2
H		0.25	0.5	0.25	
G			1	-1	
F		0.5	1	0.5	
L ₁		-0.25	0.25		
L ₂	-0.125	-0.375	0.375	0.125	
K ₁		0.125	0.75	0.125	
K ₂	0.0625	0.125	0.625	0.125	0.0625

Table 1 The wavelet filters used.

The conditional probability densities are estimated by sampling from a fixed location across the spatially aligned example images. A Parzen window method, i.e. Gaussian smoothing of the histogram, is used to convert the example neighbourhoods to a well formed distribution. We use a casual neighbourhood, i.e. we assume that the next pixel to be synthesised is

dependent only on a selection of values previously synthesised. The neighbourhood used spans multiple resolutions and includes a 12 pixel non-symmetrical half plane (NSHP) neighbourhood at the current resolution, a 3 by 3 symmetrical neighbourhood at the preceding resolution, and 1 pixel from each of the preceding resolutions (Figure 3). The use of symmetrical low-res neighbourhoods in addition to the NSHP high-res neighbourhood helps to stabilise the reconstruction, without the need for optimising the probabilities of all the pixels simultaneously. We do not assume total independence between subbands, but use all the information available from previous points in the neighbourhood to estimate each of the two coefficients at the current point.

An algorithm for estimating the conditional distribution is given below:

Algorithm 1: Calculate conditional distribution

inputs:

input image's wavelet transform (WT) I ,
array of example images' WTs J , of size M
location (x,y) , subband s
neighbourhood N ,
smoothing parameter h ,
histogram bin width bw
number of bins $bcount$

variables:

Float histogram array p of length $bcount$
Float array u for neighbourhood in I
Float array v for neighbourhood in $S[i]$

begin:

1. Initialise p to 0
2. u = values in N of $I_s(x,y)$
3. for $i = 0$ to M
 - 3.1 v = values in N of $J_s[i](x,y)$
 - 3.2 $p[J_s[i](x,y)/bw] += \text{Gaussian}(v, u, h)$
4. Smooth p with 1D Gaussian of width h and re-normalise
5. Return probability distribution p

The function $\text{Gaussian}(v, u, h)$ returns the value of a uniform multidimensional Gaussian of uniform standard deviation h centred on u and evaluated at v .

The result of applying the process described above is a probability distribution for the input pixel relative to the original group and another for the output pixel relative to the output group. The input pixel's distribution is conditioned on the values in the original image and the output distribution is conditioned on values in the output image. From these conditional distributions we calculate the cumulative distribution functions (CDF) by replacing the probabilities with the sum of all the preceding values. This gives a monotonically increasing function that maps intensities onto a value between 0 and 1. We can also invert the function to create the inverse CDF (ICDF), which maps values between 0 and 1 onto intensity. We use the CDF of the original pixel to convert the (known) original pixel value into a cumulative probability and then use the ICDF of the new pixel to map this value back into an intensity (Figure 4), giving the (new) transformed value. As the ICDF for each wavelet pixel is required only once, the

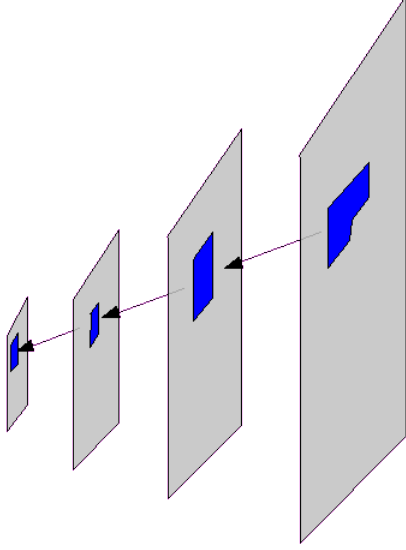


Figure 3 A diagrammatic representation of the multi-resolution neighbourhood, that includes 12 points at the current resolution (right), 9 in the preceding scale and then 1 pixel from each of the remaining lower resolutions. Only one of the 2 subbands for each scale is shown.

output value is found by simply summing the output PDF until the input CDF value is exceeded.

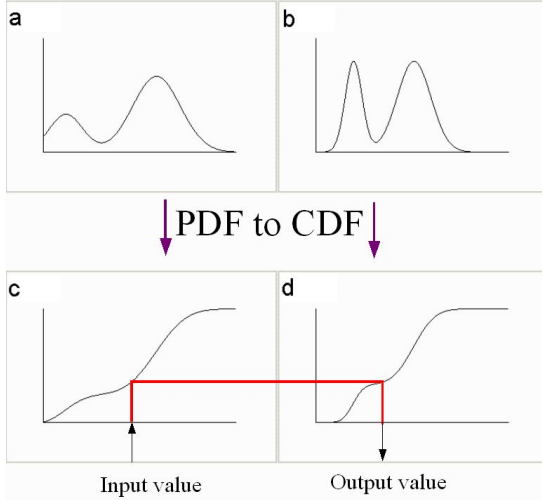


Figure 4 The input and output conditional probability distributions, (a) and (b), are converted to cumulative distributions. This provides a mapping from the original value to the new value.

When constructing prototypes [TID04] [TID05] it was discovered that the use of the “optimal” width, h_0 , for the Gaussian to smooth the distributions [SIL86] resulted in locking of the algorithm onto an individual image at a low resolution. Increasing the width of the Gaussian removed the locking problem but also resulted in blurred textures. The observation that texture information is largely dependent on the finer spatial scales indicates that we should vary the width of the

Parzen window as a function of spatial scale. We empirically derived the scaling parameter $h = (1+0.5*\text{level})h_0$ which gives a trade off between average global appearance and realistic fine-scale textures.

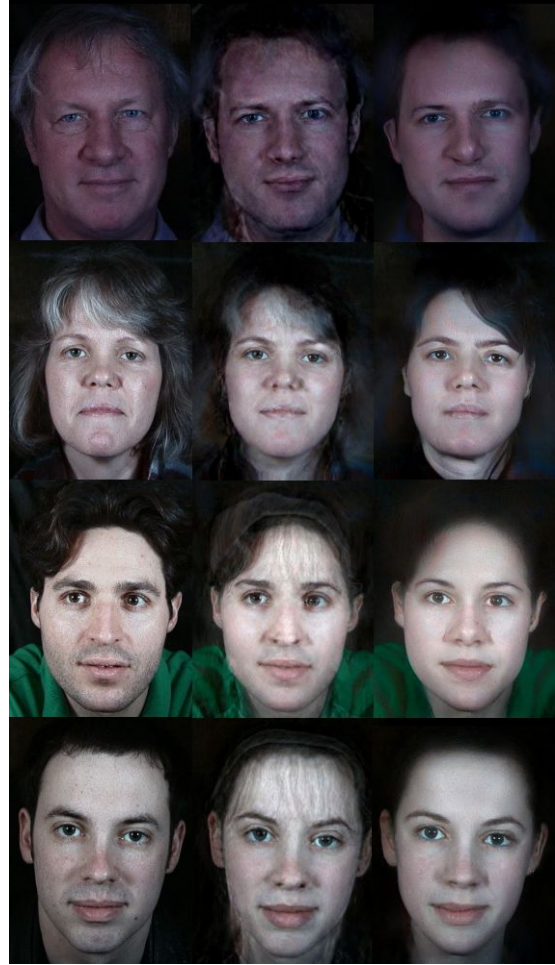


Figure 5 Examples of image transformation. Left original images, centre WM and right WMRF transformed. The top two rows are age reduction by 30 years and the bottom rows are male to female transforms.

4. Results

4.1 Transformation Results

Figure 5 shows the results of transforming individual facial images between different groups. We have deliberately picked examples for which the previous methods were unsuccessful, namely age reduction and male to female transforms. The results show that the transformations have improved considerably in terms of both the realism of the output and the effectiveness of the shift in perceived group.

These results were achieved “in-group”, i.e. the face being transformed is also a member of the source sample of images. This is not as restrictive as it might

sound, as the face can always be added to the example set if it is not already present. For out of set images, we found it necessary to clamp the output values to within 3 standard deviations of the mean of the conditional distribution of output values. Figure 6 shows the results of out-of-set transformations with and without the additional clamping. The problem with transforming out of set images is caused when a texture component is seen as highly improbable (because of the small sample size), so it can be mapped onto a highly improbable output pixel. Because of the inherent feedback in the causal model this will then influence the next pixel and so on. An alternative to clamping is to increase the sample size when building the conditional distributions, either by taking several samples from around each point in the example set or by using a larger image set. Both of these options would have an impact on the efficiency.



Figure 6 Examples of transforming out of set. The original East-Asian face images (left) are rejuvenated using European faces as examples (centre). Clamping the output values to within 3 s.d. of the conditional mean (right) improves the stability of the synthesis.

4.2 Experimental Evaluation Results

In order to validate our method we performed two perceptual experiments. These were designed to test the *realism* and *effectiveness* of the method for age transformation. Age transformation was selected because it is a commonly required transformation and it is easier to get an objective measure of its effectiveness, i.e. by rating the age.

In the first experiment subjects were asked to estimate the age of each image. Original images, images transformed using [TBP01] and images transformed using the wavelet MRF method presented here were presented to the user. The images consisted of male and female faces, divided into two approximate age categories – 39 faces 20-45 years old (16 female) and 32 faces over 45 years old (17 female). The older faces were projected into the younger age category and the younger faces were projected into the older category. Because of the large number of images to rate, the images were divided into 3 pools and users were

assigned an initial pool at random. Testers were also given the option of completing the other pools. Each pool contained the same face in each of the three conditions: real, wavelet-magnitude transformed (WM) and wavelet-MRF transformed (MRF). Thus each participant rated the age of 69-72 images. The faces were presented in a randomised order using a web-based test.

To analyse the results the participants were first filtered to remove any with a duplicate (random) ID number, or any that had responded with an age less than 15 years or greater than 95 years. This gave a minimum of 87 and a maximum of 111 participants estimating age of each face image. There was a high degree of concordance of age estimates across participants (Chronbach's Alpha >0.947 each set).

Transformations decreasing age: The MRF transform applied to rejuvenate faces produced apparent ages that were equivalent to the target age (t test comparing mean perceived age of 32 old faces transformed to decrease age with 39 faces from the younger age bracket, $t_{69}=-0.5$, $p=0.61$). The WM transform, however, failed to achieve full rejuvenation and produced apparent ages that were significantly greater than the target age ($t_{69}=7.58$, $p<0.0005$).

Transformations increasing age: The WM method produced an age increase that was slightly but not significantly in excess of the target age population ($t_{69}=1.8$, $p=0.071$). The MRF ageing transform produced images were equivalent to the target age group ($t_{69}=1.05$, $p=0.265$). The results are shown in Figure 7.

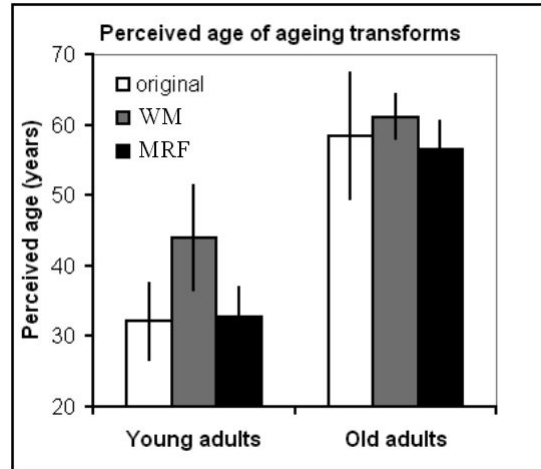


Figure 7 Comparison of perceived age of original and transformed images. The images are grouped according to the age group they should belong to after transformation. The WM method succeeds with ageing, but fails to rejuvenate sufficiently. The MRF method succeeds with both positive and negative ageing.

In the second experiment, subjects were asked to rate the same faces for realism on a 0 (very unrealistic) to 6 (very realistic) point scale. Again the images were presented in a web-based experiment and the order was randomised. Participants were excluded if they rated

original images lower than 2 for realism or if ratings SD was less than 1.0. This gave a minimum of 63 and a maximum of 92 participants estimating the realism of each face image. There was a high degree of concordance of realism estimates across participants (Chronbach's Alpha > 0.957 each set). Therefore the mean rating of each image was computed across subjects.

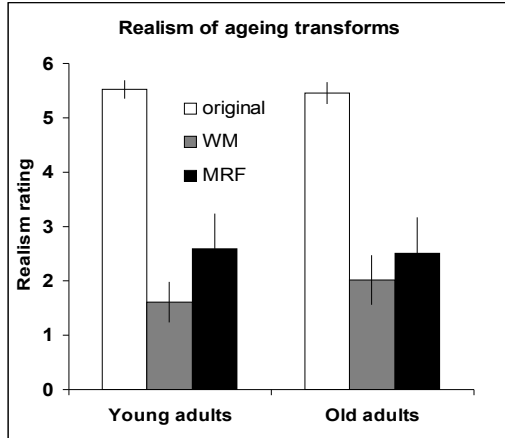


Figure 8 Realism ratings (mean ± 1 s.d.) for the real, MRF and WM transformed images.



Figure 9 TheWMRF images rated highest and lowest for realism. Average ratings: top-left (age reduction) 4.02, top-right (ageing) 3.98, bottom-left (ageing) 1.24 and bottom-right (ageing) 1.25 on a 7 (0-6) point scale.

Realism ratings were higher for MRF (mean ratings: young faces 2.6, older faces 2.5) than WM transformed images (mean ratings: young faces 1.6, older faces 2.0) both when increasing ($t_{38}=4.47$, $p<0.0005$) and reducing

apparent age ($t_{31}=8.43$, $p<0.0005$) using matched pair t-tests (Figure 8). Both MRF and wavelet magnitude methods produced images that were lower in realism compared to the original face images (mean ratings: young faces 5.5, older faces 5.5) for transforms decreasing or increasing apparent age ($t>25.1$, $p<0.0005$ each comparisons). Figure 9 shows the highest and lowest rated MRF transformed images. It appears that some of the loss in realism is due to patching of the textures, and part is due to obvious glitches caused by problems with the warping.

5. Conclusions

We have described a new wavelet-based MRF method for transforming facial images. The results demonstrate the effectiveness of the technique in terms of both realism and perceived age transformation. This method is designed principally to aid psychological research, where the ability to perform quantified shifts in perceived facial attributes has allowed the design of more effective experiments into facial perception. It is hoped that the new method will add to the range and effectiveness of these psychological experiments. In addition, these methods have potential application in the entertainment industry (e.g. for ageing of actors) and digital ageing of wanted or missing persons. Future work will include optimising the algorithm for speed, and investigating methods to avoid errors due to the warping.

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