Face Mosaicing using Multiresolution Spline:A Review

Ankit Patel, Hetal Patel

Abstract— Image Mosaicing is the act of combining two or more images. It may containe images such that no obstructive boundary exists around overlapped regions. Emphasis is given on to create a mosaic image that contains as little distortion as possible from the original images, as well as preserving the general appearance of the original images. We describe a face mosaicing scheme that generates a composite face image during enrollment based on the evidence provided by frontal and semiprofile face images of an individual. In the this scheme, the side profile images are aligned with the frontal image using a simple registration algorithm, which determine the transformation relating the two images. Multiresolution splining is then used to blend the side profiles with the frontal image, thereby generating a composite face image of the user. Experiment conducted on a CMU pose, illumination, expression (CMU PIE) database indicate that face Mosaicing, as described in this paper , offers significant benefits by accounting for the pose variations that are commonly observed in face images.

Index Terms—Face Mosaicing, Face Recognition, Gaussian & Laplacian Pyramids, Multiresolution .

I. INTRODUCTION

When multiple images are overlapped to form a single mixed image, finding an ideal image combination can be difficult. Here we can use a image mosaicing technique that can be applied to reduce this difficulty. One of the major challenges encountered by current face recognition techniques lies in the difficulties of handling varying poses. In this paper, for the same purpose we describes a scheme to generate the 2-D face mosaic of an individual during enrollment that can be successfully used to match various poses of a person's face. This face Mosaicing technique is very useful in the field of biometric such as face recognition. As one of the most important biometric techniques, face recognition has clear advantages of being natural and passive over other biometric techniques requiring cooperative subject such as fingerprint recognition and iris recognition.

Multiresolution representation technique is an effective method for analyzing information contents of signals, as it processes the signals individually at finer levels, to give more accurate results that contains much less distortion. Laplacian pyramid, Gaussian pyramid and Wavelet transform are types of Multiresolution representations. In this work, we use Laplacian pyramid using Gaussian pyramid which superiors other transforms in context of simplicity and working satisfactorily in real time domain. The work on this project will be focused on designing a model which balances the smoothness around the overlapped region and the fidelity of the blended image to the original face image.

Singh et al. [10] proposed a mosaicing scheme (MS) to form a panoramic view from multiple gallery images to cover the possible appearances under all horizontal in-depth rotations. The panoramic (namely composite) view is generated from a frontal view and rotated views in three steps, i.e. (1) view alignment, (2) image segmentation, and (3) image stitching. In the first step, views in different poses were aligned by coarse affine alignment and fine mutual information-based general alignment. The boundary blocks of 8×8 pixels for the segmentation were detected using phase correlation, which were used as the connection regions of the two views to stitch. A multiresolution splining was applied to straddle the connecting boundary of the images and the splined images were expanded and summed together to form the final composite face mosaic.

II. MULTIRESOLUTION

At some certain point in the time-frequency plane of the signal, we are not able to find the time and frequency information means we can't know what spectral components exists at any given time instant. So we have to investigate what spectral components exists at any given interval of time. This is the problem of normal resolution. We can't use the short time fourier transform (STFT) or wigner distribution because they were giving us the fixed resolution. In other words, they are not able to give good frequency and time resolution, so every spectral component is not resolved equally in STFT. Thus information provided by them was highly redundant in nature as far as reconstruction of the signal is considered. The Fig. 1 clearly shows how two images are combining to form mosaic image [5].

First image (consider it as A) is take, then it is decomposed up to N level as per requirement of user. Similarly we have taken second image (consider it as B).Now we need to design mask with same size as that of the image size. Mask is nothing but binary representation of image in to be combine images. This dummy image is used as mask for hiding appropriate part of image, i.e. Mask is a outer part of 'A' image & inner part of 'B' image. To get multi-resolved format mask for each level of decomposition we have to use low-pass filter and then sub-sampled [23].

Image is nothing but matrix of values, hence direct multiplication of mask with image is taken. Then two masked images are obtained, which are then combine to form the resultant image at each level of resolution. Now Using these entire components original image is reconstructed.

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Ankit Patel, Research Scholar, ECE Department, A. D. Patel Institute of Technology , New V.V Nagarr, Gujarat, India.
Assoc. Prof. Hetal Patel, ECE Department, A. D. Patel Institute of Technology, New V. V. Nagar, Gujarat, India.

After reconstruction we get the resultant mosaic image.

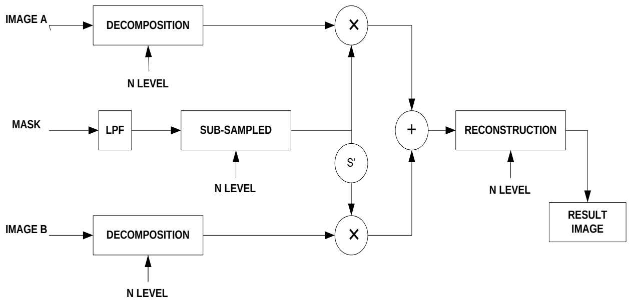


Fig. 1 N level decomposition of image

III. FACE MOSAICING

This section describes the face mosaicing algorithm used to mosaic the multiple pose images of the same face. The face is segmented (localized) from each image. A pair of face images, typically representing the frontal and profile views of an individual, are mosaiced after aligning them using a simple registration technique called affine transformation. . Registered images are mosaiced using the multiresolution splines algorithm based on Gaussian and Laplacian pyramids [14]. Multiresolution splines also perform blending as an integral part of mosaicing, thereby offering some inherent advantages.

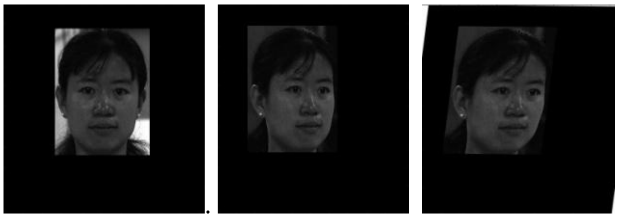
A. Registration model

Before Mosaicing the images, it is necessary to transform the multiple images obtained during enrollment into a common image domain. The process of finding the transform that aligns one image to another is called image registration. Here, three images are made available during enrollment, one is a frontal pose and another two are semi profile left and right pose images. Also, the side profile images are assumed to have a rotation of at least 30_o with respect to the frontal image in order to ensure that sufficient information about the face is available. Since the camera-to-face distance is fixed in all 3 images, a transformation to handle rotation, alignment and deformation due to various facial expressions is computed. Now for face mosaicing algorithms first the affine transformation is used as a registration model.

First, the Three blank images of size 512 x 512 are first created. Then the coordinates of the eyes and nose objects are determined in the frontal face image (this can be done using any standard eye-nose finding algorithm). The frontal image is placed on one of the blank image spaces such that its nose coordinates are at the center, shown in Fig. 2.Similarly, the three coordinates (two eyes and one nose) are located in the side-profile face images. Based on their respective nose coordinates, these images are placed in the two remaining blank image spaces Based on the positions of the eyes and the nose, a terrain transform is used to align each of the side profile images with the corresponding frontal face image as shown in Fig. 2.

To represent affine transformations with matrices [30], we can use homogeneous coordinates. This means representing a 2-vector (x, y) as a 3-vector $(x, y, 1)$, and similarly for higher

dimensions. Using this system, translation can be expressed with matrix multiplication. The functional form :



(a) (b) (c)

Fig.2. Image registration using the affine transformation model. Frontal and profile images are first placed at the center of a 512×512 image space.(a)Input frontal image. (b)Input profile image. (c)Profile image registered with respect to the frontal image.

$$x' = x + t_x \tag{1}$$

$$y' = y + t_y \tag{2}$$

is becomes

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{3}$$

For scaling (that is, enlarging or shrinking), we have

$$x' = s_x . x \tag{4}$$

$$y' = s_y . y \tag{5}$$

The matrix form is

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{6}$$

When S_x S_y $=1$, then the matrix is a squeeze mapping and preserves areas in the plane. For rotation by an angle θ counter clockwise about the origin, the functional form is

$$x' = x\cos\theta - y\sin\theta \tag{7}$$

$$y' = x\sin\theta + y\cos\theta \tag{8}$$

Written in matrix form, this becomes

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{9}$$

B. Mask design

The challenge in face mosaicing is to ensure that salient facial features (viz., eye, nose, chin, face contour, etc.) are not distorted during the blending process [5][10][12]. In this regard we make the following two observations: (a) the seam in the upper region of the face is mostly vertical; (b) the seam in the lower portion of the face has to accommodate the user's

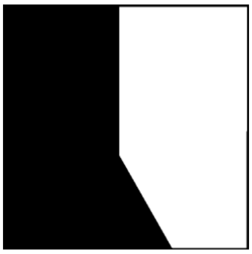


Fig. 3. Mask designed from right pose image

chin which is slightly slanted. Thus, we have develop a binary mask that defines the regions pertaining to the frontal and side profiles to be retained in the composite image. The shape and size of the mask varies across individuals and depends on the rotation of the face. Thus, this is a dynamic mask generated at runtime. Fig. 3 shows an example of the mask generated from the right profiles of a user. Note that the mask presents a strict boundary between the 2 images. In order to 'soften' this, we subject the mask to a Gaussian weighting function.

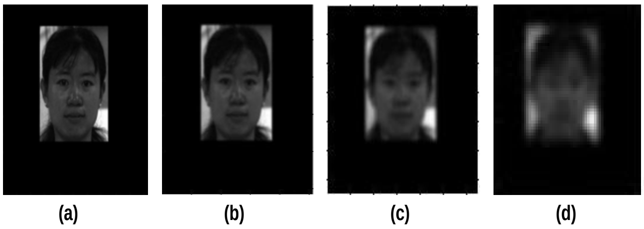


Fig. 4. Levels in the Gaussian pyramid expanded to the original size to see the effects of the low pass filter (a)Level 0 (b) Level 1 (c) Level 2 (D) Level 3

C. Gaussian pyramid generation

For blending the two images into a single mosaic, we use multiresolution splines [14]. Image splining (i.e., blending) can be performed based on a simple spline-weighting function1 straddling the boundary of the two images, but the quality of the stitched image depends on the step size (or window) that is chosen. A large step size may lead to blurring, whereas a small step size may result in discontinuities at the boundary.To overcome this problem, Burt and Adelson [14] used multiresolution splines to determine different step sizes for the various frequency components constituting the boundary. The crux of this technique involves computing a Gaussian pyramid of subimages, followed by a Laplacian pyramid, based on the two images to be mosaiced; the pyramid structure is used to estimate the spline weighting function that relies on the frequency-domain information of the image. A sequence of low-pass-filtered images is obtained by iteratively convolving each of the constituent images with a 2-D Gaussian filter kernel. The Resolution and sample density of the image between successive iterations (levels) is reduced, and therefore, the Gaussian kernel operates on a reduced version of the original image in every iteration. The resultant images G0,G1, . . . , GN may be viewed as a "pyramid," with G0 having the highest resolution (lowermost level) and GN having the lowest resolution (uppermost level). Let w(m, n) represent the Gaussian kernel with dimensions of 5 × 5 and a reduction factor of 4. The reduce operation can be written as

$$\text{Reduce}\,(I(i,j)) = \sum_{m=1}^{5}\sum_{n=1}^{5} w(m,n) I(2j+m, 2j+n) \tag{10}$$

A Gaussian pyramid G_l is defined as

$$G_0 = i \tag{11}$$

$$G_l = Reduce[G_{l-1}],\quad 0<1<\mathrm{N} \tag{12}$$

So, in this method,Gaussian pyramid level that reduces the original size of image by and also the Gaussian kernel is applied with it to blurr the images. In Fig. 4 we shows the images after expand it to the original size

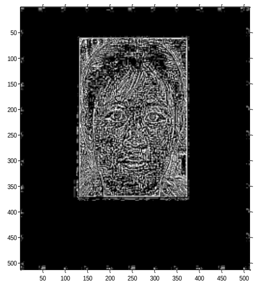


Fig. 5. First level of laplacian pyramid

D. Laplacian pyramid generation

The multiresolution spline, as described in [14], requires bandpass images, as opposed to low-pass images. Bandpass images are computed by interpolating (resizing) the image at each level of the Gaussian pyramid and then subtracting it from the next lowest level. This results in a sequence of bandpass images that may be viewed as a Laplacian pyramid ($L0, L1, \ldots, LN$), as shown in Fig. The term Laplacian is used since the Laplacian operator resembles the difference of Gaussian-like functions. These bandpass images are a result of convolving the difference of two Gaussians with the original image. The steps used to construct this pyramid can also be used to exactly recover the original image. The process described previously may be summarized as follows:

$$L_l = G_l - Expand[G_{l+1}]\ ,0 \le 1 \le \mathrm{N} \tag{13}$$

Here, the Expand [·] operator interpolates a low-resolution image to the next highest level and can be written as

$$G_{l,k}(i,j) = 4\sum_{m=-2}^{2}\sum_{n=-2}^{2} w(m,n) G_{l,k-1}\left(\frac{i-m}{2}, \frac{j-n}{2}\right) \tag{14}$$

Note that *Gl,k* in (14) denotes "expanding" *Gl k* number of times. Various features of the face are segregated by scale in different levels of the pyramid. The textural features of face are preserved over multiple levels of the pyramid. Let $L1$ and $L2$ represent the Laplacian pyramids of the two images that are being splined (i.e., blended).

Let *GR* be the pyramid associated with the Gaussian-weighted mask discussed in previous Section II(2). The multiresolution spline *LS* is then computed as

$$LS_l(i,j) = GR_l(i,j)L_{1_l}(i,j) + (1 - GR_l(i,j))L_{2_l}(i,j) \tag{15}$$

where *l* is the level of the pyramid. Fig. 5 shows the first level of laplacian pyramid. The splined images at various levels are expanded and summed together to obtain the final face mosaic.

IV. EXPERIMENTAL RESULTS

This section gives brief idea about what how face mosaicing can be practically implemented. For this the image used is having the dimensions of 512x512. At first the image is decomposed into two stages with coefficient from all the stages are saved. Then designing the mask, we have selected the mask size same as image size. Now a mask has to be designed as per the requirement. In this case, we want to mosaic the face image of front and semi profile images shown in Fig. 6. So, we have designed a mask which has matrix in which all the coefficients are 1(white) for the face region.

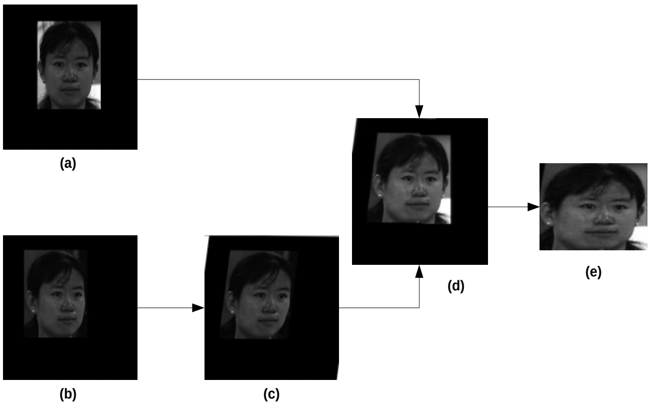


Fig. 6. (a)Frontal Pose (b) Right Pose (c) Registered right pose with respect to front pose (d) Mosaiced face (e) cropped face for further use

Then the original image is multiplied with the mask to obtain the image in result. So, while designing the mask, we need to take complement of the mask that design for previous section. Actual Mosaicing is done with result images from stages one and two which gives final result image. This process is shown in fig 6.

V. CONCLUSION

In this article, we describes a face mosaicing algorithm that uses a front and side pose face images for mosaic into a single face image. Given multiple images of a face during enrollment, the Mosaicing algorithm blends them into a single entity. This algorithm which generates a mosaic face that can be very useful in the pose-invariant face recognition algorithms.

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AUTHORS PROFILE

Mr. Ankit N. Patel, received his Bachelor Degree of Engineering in Electronics and communication in year 2010 from Government Engineering college, Gandhinagar, Gujarat University. He is also pursuing Master Degree in Signal processing & Communication form A. D. Patel Institute of Technology, New V.V. Nagar, Gujarat Technological university. His area of interest includes Image and Signal processing.

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