

IMAGE FUSION

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1 INTRODUCTION

image fusion(IF) is a technique to combine the registered images to increase the spatial resolution of acquired low detail multi-sensor images and preserving their spectral information. The benefiting fields from IMAGE FUSION are: Military, remote sensing, machine vision, robotic, and medical imaging, etc. The fused image would provide enhanced superiority image than any of the original source images. Dependent on the merging stage, could be performed at three different levels viz. pixel level, feature level and decision level. In this paper, pixel-level-based IF is presented to represent a fusion process generating a single combined image containing an additional truthful description than individual source image.

2 TECHNIQUES OF IMAGE FUSION

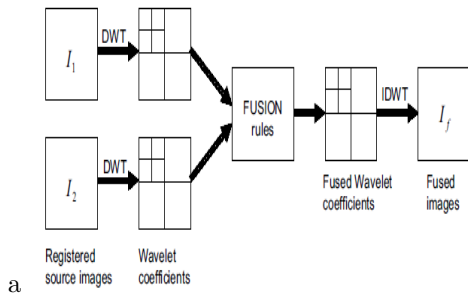
- 1.principal component analysis(PCA)
- 2.wavelet transform

2.1 principal component analysis(PCA)

The PCA involves a mathematical procedure that transforms a number of correlated variables into a number of uncorrelated variables called principal components. It computes a compact and optimal description of the data set. The first principal component accounts for as much of the variance in the data as possible and each succeeding component accounts for as much of the remaining variance as possible. First principal component is taken to be along the direction with the maximum variance. The second principal component is constrained to lie in the subspace perpendicular of the first. Within this subspace, this component points the direction of maximum variance. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on. The PCA is also called as Karhunen-Loève transform or the Hotelling transform. The PCA does not have a fixed set of basis vectors like FFT, DCT and wavelet etc. and its basis vectors depend on the data set.

2.2 wavelet transform

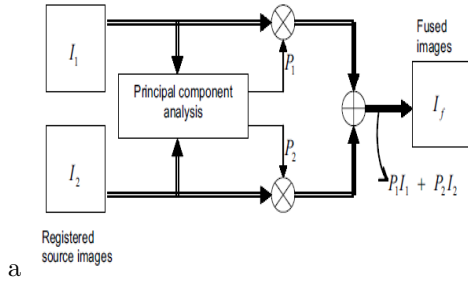
Wavelet theory is an extension of Fourier theory in many aspects and it is introduced as an alternative to the short-time Fourier transform (STFT). In Fourier theory, the signal is decomposed into sines and cosines but in wavelets the signal is projected on a set of wavelet functions. Fourier transform would provide good resolution in frequency domain and wavelet would provide good resolution in both time and frequency domains. Although the wavelet theory was introduced as a mathematical tool in 1980s, it has been extensively used in image processing that provides a multi-resolution decomposition of an image in a biorthogonal basis and results in a non-redundant image representation. The basis are called wavelets and these are functions generated by translation and dilation of mother wavelet. In Fourier analysis the signal is decomposed into sine waves of different frequencies. In wavelet analysis the signal is decomposed into scaled (dilated or expanded) and shifted (translated) versions of the chosen mother wavelet or function



3 IMAGE FUSION ALGORITHM

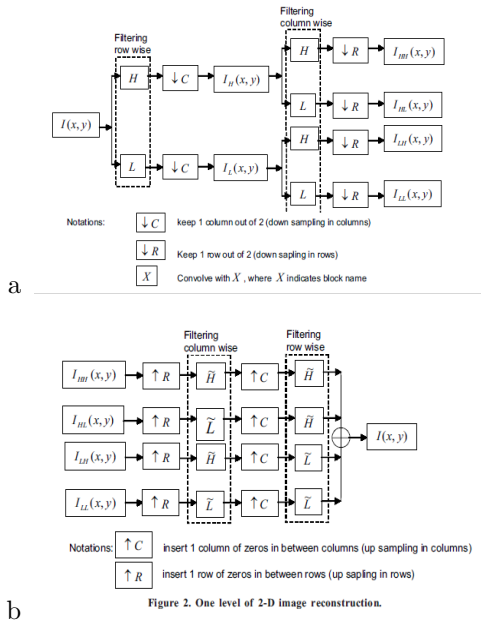
3.1 principle component analysis (PCA)

1. Organise the data into column vectors. The resulting matrix Z is of dimension $2 \times n$
2. Compute the empirical mean along each column. The empirical mean vector Me has a dimension of 1×2 .
3. Subtract the empirical mean vector Me from each column of the data matrix Z . The resulting matrix X is of dimension $2 \times n$.
4. Find the covariance matrix C of X i.e. $C = XX^T$ mean of expectation = $cov(X)$
5. Compute the eigenvectors V and eigenvalue D of C and sort them by decreasing eigenvalue. Both V and D are of dimension 2×2 .
6. Consider the first column of V which corresponds to larger eigenvalue to compute P_1 and P_2



3.2 wavelet transform

Wavelet separately filters and down samples the 2-D data (image) in the vertical and horizontal directions (separable filter bank). The input (source) image is $I(x, y)$ filtered by low pass filter L and high pass filter H in horizontal direction and then down sampled by a factor of two (keeping the alternative sample) to create the coefficient matrices $Il(x, y)$ and $Ih(x, y)$. The coefficient matrices $Il(x, y)$ and $Ih(x, y)$ are both low pass and high pass filtered in vertical direction and down sampled by a factor of two to create sub bands (sub images) $ILL(x, y)$, $ILh(x, y)$, $IHL(x, y)$, and $IHH(x, y)$. The $ILL(x, y)$, contains the average image information corresponding to low frequency band of multi scale decomposition. It could be considered as smoothed and sub sampled version of the source image $I(x, y)$. It represents the approximation of source image $I(x, y)$, $ILh(x, y)$, $IHL(x, y)$, and $IHH(x, y)$, are detailed sub images which contain directional (horizontal, vertical and diagonal) information of the source image $I(x, y)$, due to spatial orientation. Multi-resolution could be achieved by recursively applying the same algorithm to low pass coefficients from the previous decomposition



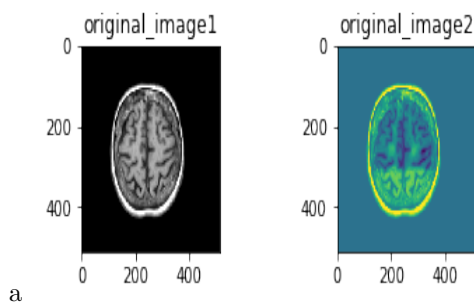
4 PROGRAMS AND ITS RESULTS

4.1 principal component analysis(PCA)

```
from PIL import Image
import numpy as np
from sklearn.preprocessing import StandardScaler
import pandas as pd
from scipy.linalg import eigh

img1 = Image.open('s1.gif').convert('L')
img2 = Image.open('ss2.gif').convert('L')
i1 = np.array(img1)
i2 = np.array(img2)
img_array1 = pd.DataFrame(np.array(img1).flatten())
img_ary = pd.DataFrame(np.array(img1).flatten())
img_array2 = pd.DataFrame(np.array(img2).flatten())
img_ary.insert(1, '',img_array2)
img_matrix = img_ary
std_data = StandardScaler().fit_transform(img_matrix)
data = np.matmul(std_data.T,std_data)
cov_matrix = np.cov(data)
val,vec = eigh(cov_matrix,eigvals=(1,1)) #std_data.shape (262144, 2)
v=np.sum(vec)
p1 = vec[0] / v
p2 = vec[1] / v
r1 = p1 * i1
r2 = p2 * i2
r = r1 + r2
img = Image.fromarray(r)
import matplotlib.pyplot as plt
plt.subplot(2,2,1),plt.imshow(img1),plt.title('original_image1')
plt.subplot(2,2,2),plt.imshow(img2),plt.title('original_image2')
#plt.imshow(r)#,cmap='gray')
plt.imshow(r)
```

4.1.1 results



4.2 wavelet transform

```
from PIL import Image
import pywt
import numpy as np
import matplotlib.pyplot as plt
img1 = Image.open('s1.gif').convert('L')
img2 = Image.open('ss2.gif').convert('L')
img1_ary = np.array(img1)
img2_ary = np.array(img2)
```

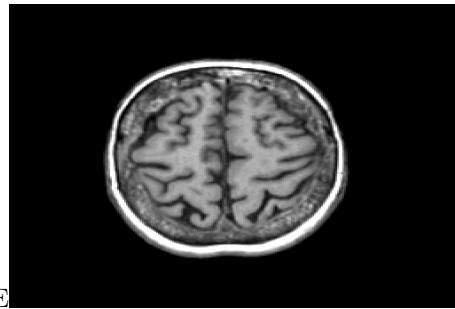
```

import pywt
coeff1 = pywt.dwt2(img1_ary,wavelet='haar')
coeff2 = pywt.dwt2(img2_ary,wavelet='haar')
LL1, (LH1, HL1, HH1) = coeff1
LL2, (LH2, HL2, HH2) = coeff2
def fuse_coeff(coeff1, coeff2):
    coeff = (coeff1 + coeff2) / 2
    return coeff
fusedCoef = []
for i in range(len(coeff2)-1):
    if(i == 0):
        fusedCoef.append(fuse_coeff(LL1,LL2))
    else:
        c1 = fuse_coeff(coeff1[i][0], coeff2[i][0])
        c2 = fuse_coeff(coeff1[i][1], coeff2[i][1])
        c3 = fuse_coeff(coeff1[i][2], coeff2[i][2])

        fusedCoef.append((c1,c2,c3))
fusedImage = pywt.waverec2(fusedCoef, wavelet='haar')
plt.imshow(fusedImage)#,cmap='gray')

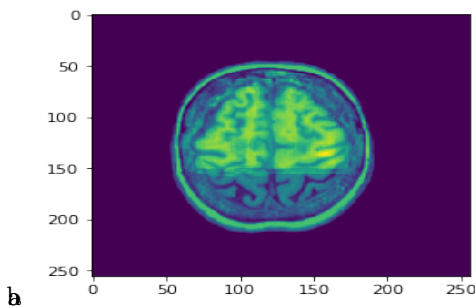
```

4.2.1 results



INPUT IMAGE

OUTPUT IMAGE



5 CONCLUSION

Pixel-level image fusion using wavelet transform and principal component analysis are implemented in PC MATLAB. Different image fusion performance metrics with and without reference image have been evaluated. The simple averaging fusion algorithm shows degraded performance. Image fusion using wavelets with higher level of decomposition shows better performance in some metrics while in other metrics, the PCA shows better performance. Some further investigation is needed to resolve this issue.

6 REFERENCE

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