Content-Adaptive Data Fusion

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Abstract. We propose a novel image fusion scheme based on independent component analysis in which image / information is fused aimed at information maximization. In the scheme, a novel algorithm is presented which, based on specific fusing images, determines adaptively a specific weight for linear fusion of images using ICA. The scheme is established on the ICA maximum information principles and offers an efficient and adaptive image fusion process with the robustness under various fusion situations.

1 Introduction

Image fusion is to combine images of an underlying scene captured by multiple sensors to synthesize a composite image. Different sensors provide different information about the scene and are effective in different environmental conditions. The aim of image fusion is to create a fused image which not only is visually acceptable (figure 2 shows a misaligned face fusion) by the human visual system (HVS) but also captures maximum amount of the information offerred by the images generated from different sensors. A TV and IR image fusion system is illustrated in figure 1.

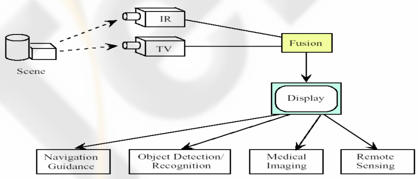

Fig. 1. TV & IR Image fusion.

2 Image Fusion Schemes

There are a number of approaches to image fusion, most of which are often classified into pixel-based or feature based-approaches.

The first and simplest image fusion method is the fusion-by-averaging in which the fused image is synthesized by averaging corresponding pixels of the sensors images.

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An advantage of fusion-by-averaging is that it is very computationally effective. However, averaging works poorly when feature mismatching occurs in fusion images.

A more popular pixel-based image fusion technique is PCA-based image fusion. The technique makes use of *Principle Component Analysis* to decompose the images into principle components and the PCs are fused together to obtain the PCA fused image [1-2].

Feature-based image fusion schemes transform images into *features* such as edges, and perform fusion in the feature domain. Since different features are important at different levels of resolution, multi resolution representations of images are normally generated. And fusion in feature-based techniques is carried out on the multi resolution pyramid [3].

Fig. 2. An example of misaligning face images.

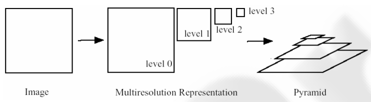


Fig. 3. Multi scale Decomposition of images.

One of the most popular feature-based schemes is the *Laplacian* pyramid technique. In *Laplacian* pyramid fusion approach, a *Gaussian* multi-scale pyramid is built for each image. Then a *Laplacian* transformation is applied on the *Gaussian* pyramids to form *Laplacian* transformed pyramids of images. Fusion is then applied on *Laplacian* pyramids to obtain the fused *Laplacian* transformed pyramid. By exploiting the perfect reconstruction characteristic of *Laplacian* transform, a fused image can be obtained from the fused pyramid using an inverse *Laplacian* transform. Over the years, there has been numerous enhancement added to the original scheme [5]

Toet *et al.* [4] introduced a contrast based image fusion technique which preserves local luminance contrast in the sensor images. The technique is based on selection of image features with maximum contrast rather than maximum magnitude. It is motivated by the fact that the human visual details to a human observer. The pyramid decomposition used for this technique is related to luminance processing in the early stages of the human visual system which are sensitive to local luminance contrast. Fusion is performed using the multi-resolution contrast pyramid.

Wavelet based image fusion techniques, as shown in figure 3, has been a focus recently. The wavelet transform decomposes the image into baseband at the coarsest scale and highbands at different scales. The baseband contains the average image information whereas the various highbands contain directional information due to spatial orientation. Higher absolute values of wavelet coefficient in the highbands correspond to salient features such as edges, lines, etc. Li *et al.* [6] performed fusion in the wavelet transform using a selection-based rule, while Wilson *et al.* [7] suggested an extension to wavelet-based fusion using a perceptual-based weighting.

While a number of image fusion approaches has been proposed, the issues of retaining information in the fused images has rarely been touched.

3 ICA Analysis and Image Fusion

Different types of sensors provide different types of information. In some cases, some information (redundant information) is provided by several types of sensors; in other cases, some information (complementary information) is produced uniquely by one type of sensor. In terms of information, the aim of image fusion is twofold: on one hand it aims to improve reliability (by redundant information), and on the other hand, it tries to improve capability (by making use of complementary information). Hence, the problem in image fusion is how to ensure the fused image retains the maximum information from the original images (figure 4).

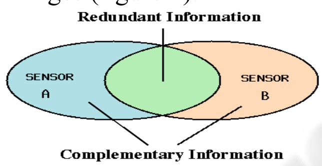


Fig. 4. Information in Image fusion.

ICA-based image fusion promises to provide maximum information, in comparisons to other linear fusion of images (even to its sibling PCA) and offers some interesting aspects on fused images.

Independent components analysis (ICA) is a mathematical method for separating a signal into its most probable additive subcomponents supposing the statistical independence of the source signals. In real environment, different signals are often statistically independent and ICA techniques can be applied to separate original signals from a mixture of those signals. ICA is closely related to Blind Source Separation (BSS) techniques.

ICA is often considered developed from Principal Component Analysis (PCA). PCA is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns search in high-dimensional data set is extremely difficult, where the luxury of graphical representation is not available, PCA is a powerful tool for analyzing data. Figure 5 provides a graphical representation of a two-dimensional data set and its 2 *principle components*

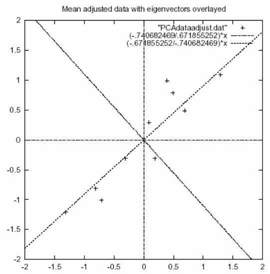


Fig. 5. An example of Principal Analysis.

Generally if the data has n dimensions, we will have n principle components. The components can be expressed as vectors (eigenvector) in the data space. And PCA techniques ensure all the eigenvectors are perpendicular.

The principle components will give us the original data solely in terms of the vectors we chose. Our original data set has two coordinates, represented by (x, y). It is possible to express data in terms of any two axes. If these axes are perpendicular, then the expression is the most efficient. This was why PCA techniques ensure that eigenvectors are always perpendicular to each other. Thus, we represent data in the space of the two eigenvectors instead of (x, y).

Theoretically there are two (principle) components, but it is possible ignore components of lesser significance. In such cases, some information is lost, but if the eigenvalues are small, not much is being lose. The advantage is that the final data set will have fewer dimensions than the original. In fact, this is the whole concept of PCA based data compression.

It has been noted that the eigenvector with the highest eigenvalue is the principle component of the data set. In our example, the eigenvector with the larges eigenvalue was the one that pointed down the middle of the data. It is the most significant relationship between the data dimensions.

When all the principal components are retained (no compression), the PCA model is invertible. Once the principal components y_i have been found, the original observations can be readily expressed as their linear functions as $x = \sum_{i-1}^{n} y_i x_i$, and also the principal components are simply obtained as linear functions of the observations: $y_i = w_i^T x.$

Both PCA and ICA approaches try to extract components out of a signal; however, there are essential differences between them. PCA is a purely second-order statistical method where only co-variances between the observed variables are used in the estimation, assuming that the observed variables are *Gaussian* and also uncorrelated, which also implies the independence in the case of *Gaussian* data.

Contrast to PCA, ICA is a similar generative latent variable model, where the factors or independent components are assumed to be statistically independent and non-*Gaussian* – a much stronger assumption that removes the rotational redundancy of the PCA (factor analysis) model.

Given a mixture of components (signals), extraction of the independent components (independent signals) from the mixture can be accomplished based on either of the following approaches:

Nonlinear decorrelation

Components y_i and y_j are independent if the components y_i and y_j are uncorrelated, *and* the transformed components $g(y_i)$ and $h(y_j)$ are uncorrelated, where $g()$ and $h()$ are some suitable nonlinear functions.

The question is: what are suitable functions? The answer can be explored using the principles of estimation theory and information theory. Estimation theory proposes maximum likelihood method whereas information theory recommends the use of mutual information as the measures for independence. It is proven as expected that mutual information and maximum likely-hood are innately connected.

Non-Gaussianity

The second approach is based on the following that according to the central limit theorem, sums of non-*Gaussian* random variables are closer to *Gaussian* than the original ones. Therefore, if we have a linear combination $y = \sum b_i x_i$ of the observed mixture i variables (which, due to the linear mixing model, is a linear combination of the independent components as well), this will be maximally non-Gaussian if it equals to one of the independent components. This is because if it were a real mixture of two or more components, it would be closer to a Gaussian distribution, due to the central limit theorem [8].

Thus, the problem of extracting independent components is equivalent to finding the local maxima of non-gaussianity of a linear combination $y = \sum b_i x_i$ under the constraint that the variance of y is constant. Each local maximum gives one independent component.

To measure non-*Gaussian* practically, we could use, for example, the kurtosis, a higher-order cumulant, which is a form of generalizations of variance using higher-order polynomials. Cumulants have interesting algebraic and statistical properties, leading to their essential roles in the theory of ICA.

Bell *et al* [9] proposed using entropy as the measurement of information.

$$E = \sum p * \log(p) \tag{1}$$

And the gradient training rule has been proven to be

$$\Delta W \propto \left[W^T\right]^{-1} + (1-2y)x^T \tag{2}$$

The inspiration behind the ICA-based image fusion can be illustrated in figure 6. In the figure PCA approaches shows vertical projection. While the projection shows the *principle component* of the randomness, the clustered structure of the data will completely be lost. In fact, clustering structure is not visible in the co-variance or correlation matrix on which PCA is based. ICA promises to overcome these problems.

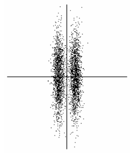


Fig. 6. What is interesting linear fusion?

Bell *et al* [10] reported an approach in which images can be expressed as a combination of independent components. Mathematically we have:

$$I = W * C \tag{3}$$

where I is the transformed signals of the image, C is the independent (information) components of the image and W is the trained weights, respectively.

If we apply ICA onto the mixture of two fusing images, we will have

$$(I_1 \mid I_2) = W * \left(C_1 \mid C_2\right) \tag{4}$$

Consider a linear fusion of images, we have

$$(a * I_1 + b * I_2) = W * \left(a * C_1 + b * C_2\right) \tag{5}$$

The simple transformation shows that linear fusion of images actually equal to the fusion of information (Independent Components) from both images. From the perspective of information, the fusion is mainly aimed at retaining maximum information from original images.

Linear image fusion is not only the fusion of information; it also offers the superb efficiency computation and ensures the output of fusion will be a visually acceptable.

However, as evidenced in fusion-by-averaging, a linear fusion scheme using fixed weights would be ineffective in producing good results for diverse fusing images. Therefore an algorithm, which can dynamically adapt to the fusing images and adjust the weights so that maximum information can be retained from fusing images, is in need, motivating the design of the ICA-based image fusion. The framework of the ICA-based image fusion is briefed as follows and illustrated in figure 7.

1. *Transform original images to signals (each image become one signal 1xN)*
2. *Combine all signals (images) into one mixture of signals (nxN: n: number of images)*
3. *Running ICA on the mixture of signals to gain the highest entropy (most information) signals output*
4. *Retransform the calculated signals to become algorithm's output fused image.*

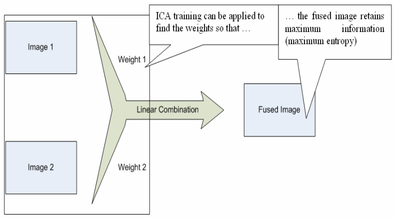


Fig. 7. ICA in image fusion concept.

The proposed ICA approach in image fusion has the following advantages. The fused image retains the maximum information from the fusing images. As discussed in section 3, the ICA algorithm ensures that each extracted output is the local maximum of entropy or maximum of information. The characteristic is obtained based on adaptive neural network training using the fusing images as training inputs which leads to the second advantage of the proposed method.

The linear combination weighting of fusing images is determined adaptively depending on specific given fusing images. This gives the approach great effectiveness in solving the fusion problem dynamically and ensures that a maximum information fused image will be produced regardless of fusing images.

The method also provides an efficient solution to the image fusion problem. As we can see, the ICA training is the most expensive part of the fusion scheme. The ICA training performance is largely dependent on the number of images to be fused. Fortunately, the number of fusing images is normally limited at 2-3 images. At unoptimized code and learning step size, the algorithm usually takes less than a minute to produce the fusion result. It can also be expected that for the video fusion, the ICA training may be performed only for each of *Group of Pitcures* to determine the fusion weights, aimed at achieving a realtime video fusion performance.

4 Experimental Results

We have used a simple ICA algorithm for the image fusion of various types of images, including facial images (with and without glasses), remote sensing & surveillance images, multi focus images. The visual comparisons of pre-fused and post-fused images are given in figure 8.

The right most images are the fusion results of the two corresponding left side images

Fig. 8. Fusion images using ICA.

The fused images by the proposed ICA approach are compared to those produced by other approaches. The criterion for comparison is the *entropy,* calculated by equation (1), of fused images. The fused images as well as Matlab implementation is available on our website. As showed in figures 9 and 10, ICA outperforms performance other linear fusion approaches such as averaging or PCA. While for other feature-based approaches, ICA performance is competitively comparable. The visual comparisons between the ICA-based fusion scheme and several other fusion techniques, namely, PCA-based, averaging, Laplacian, contrast-based and wavelet-based fusions, are shown I figure 11.

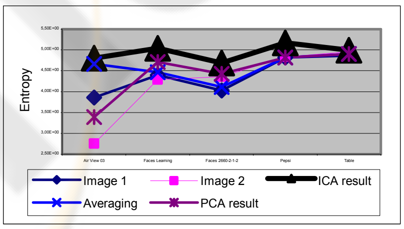


Fig. 9. ICA vs. averaging & PCA.

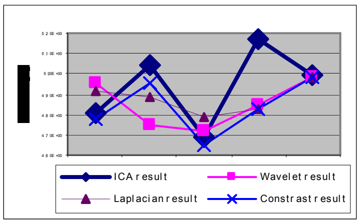
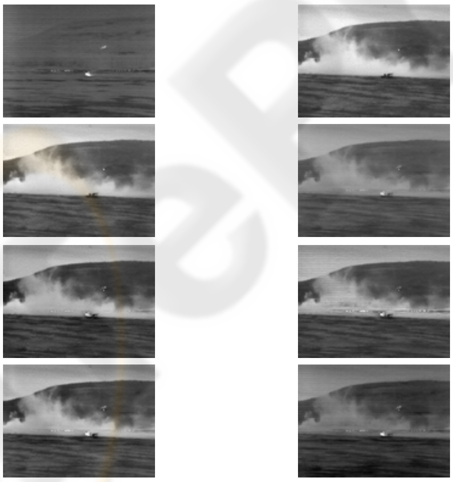


Fig. 10. ICA vs. feature based approaches.

5 Conclusions

We proposed a novel image fusion scheme based on optimizing the weighting of the fusing images using ICA. It is showed that images are combination of the independent components and that the r fusion retains information from all the fusing images. A novel algorithm is presented which, based on specific fusing images, determines adaptively a specific weight for the linear fusion of images. The algorithm is based on ICA maximum information principles and provides a fast and efficient process to the problem of image fusion. The adaptive training offers the effectiveness in achieving excellent fused image and shows the robustness of the scheme under various fusion situations.



1: Original IR Image 2: Original TV image

3: PCA fused image 4: Averaging fused image

Fig. 11. Visual comparision of results.

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