Phase-Adaptive Image Signal Fusion using Complex-valued Wavelets

Alexander Wong, David Clausi, and Paul Fieguth
Systems Design Engineering, University of Waterloo, Canada
$\{$*a28wong,dclausi,pfieguth*$\}$*@engmail.uwaterloo.ca*

Abstract

This paper presents a novel method for medical image signal fusion using complex-valued wavelets to enhance the information content in the fused signal from a perceptual manner. The proposed method introduces an adaptively weighted aggregation of signal characteristics based on the phase characteristics of medical image signals. The proposed method exploits the phase characteristics of the image signals to adaptively accentuate important anatomical and functional characteristics captured by each image signal during the signal fusion process. Experimental results show that the proposed method can improve the visualization of important anatomical and functional characteristics from different medical image signals in the fused image signal when compared with non-adaptive image signal fusion methods.

1 Introduction

Signal fusion is the process of combining multiple signals from various sources into a single composite signal. Recent research activity in multimodal image signal fusion has been focused on medical image signal fusion. Image signals acquired using devices such as x-rays, CT (Computed Tomography), MR (Magnetic Resonance), and PET (Positron Emission Tomography) provide unique information about the anatomical and functional characteristics of the human body that are important for disease diagnosis. For example, CT provides detailed bone structure information, MR provides detailed tissue information, and PET provides detailed information about bodily functions such as metabolism. However, medical image signals acquired using a single imaging modality may be inadequate for the diagnosis of disease. Given the complementary nature of these signals, a more complete visualization of a patient's health can be obtained by integrating important information content from each of the imaging modalities into a single fused image signal.

Various techniques have been proposed for the purpose of image signal fusion. Conventional image signal fusion methods include color fusion [1], and image signal fusion using mathematical and morphological operators (i.e., add/average, subtract, and, or, max, min) [2]. Some recent work have focused on a statistical approach to the problem of image signal fusion [3, 4]. While considerably more complex, this approach can provide improved visualizations when compared to color fusion and simple operator-based methods since the contribution of information from the individual image signals are weighted based on their statistical significance. Other recent work have focused on wavelet-based fusion methods [5, 6], where the wavelet coefficients are considered during the fusion process. These methods utilize the statistical properties of the wavelet coefficients to provide improved visualizations of details in the images.

Much of the existing literature in medical image signal fusion have focused on a statistical perspective to the problem, with the enhancement of information content in the fused image signal from a perceptual perspective largely unexplored. This is very important since the goal of medical image signal fusion is to aid clinicians in the diagnosis of disease. By accentuating important anatomical and functional characteristics from the individual medical image signals, the fused image signal should provide better insight on the condition of a patient. In this paper, we propose a novel approach to medical image signal fusion that adapts the construction of the fused image signal based on anatomical and functional characteristics captured by a medical image signal using phase characteristics obtained from complex-valued wavelets.

This paper is organized as follows. The proposed medical image signal fusion method is described in Section 2. Experimental results are presented and discussed in Section 3. Finally, conclusions are drawn in Section 4.

978-1-4244-2175-6/08/$25.00 ©2008 IEEE

2 Novel Fusion Method

Suppose that we are given n 2-D signals $f_1(x,y), f_2(x,y), ..., f_n(x,y)$ that have been acquired using different imaging modalities and aligned together using the multi-modal registration technique proposed in [7]. The goal of multimodal image signal fusion is to integrate the information content of the individual image signals into a single fused image signal. This can be expressed as:

$$g(x,y) = H(f_1(x,y), f_2(x,y), ..., f_n(x,y)) \quad (1)$$

where g is the fused image signal and H is the signal fusion process. A simple but effective method for image signal fusion is to perform a simple normalized aggregation of the image signals. This can be expressed as:

$$g(x,y) = \frac{1}{n}\sum_{i=1}^{n} f_i(x,y) \quad (2)$$

The main problem with this simple normalized aggregation of image signals is that all information content within the image signals are treated the same. Therefore, important anatomical and functional characteristics that are prominent within a particular imaging modality are treated no differently than unimportant characteristics within other imaging modalities. Since clinicians utilize important anatomical and functional characteristics for the purpose of disease diagnosis, it is intuitive that such characteristics are accentuated and emphasized within the individual image signals. To achieve this goal, a normalized weighted aggregation approach to image signal fusion can be used to accentuate such characteristics during the image signal fusion process. This can be expressed as:

$$g(x,y) = \frac{\sum_{i=1}^{n} w_i(x,y) f_i(x,y)}{\sum_{i=1}^{n} w_i(x,y)} \quad (3)$$

where $w_i(x,y)$ is the weight assigned to information content at (x,y) in signal i. Since the underlying goal of the proposed method is to enhance the visualization of information content from a perceptual perspective, it is intuitive that the assigned weights are associated with the importance of anatomical and functional characteristics within a signal based on human perception.

To adaptively adjust weights based on the importance of anatomical and functional characteristics within an image signal, a weighting function that reflects the perceptual sensitivity of the human vision system to such characteristics is necessary. An important characteristic in context of the human vision system is phase coherence [8, 9, 10]. This is based on the theory that perceptually important signal characteristics such as important anatomical and functional characteristics occur at points in a signal where there is maximal phase order, and has subsequently been reinforced based on psychophysical evidence [8]. A major advantage of this approach is that, since only phase information is utilized, it is insensitive to the underlying amplitudinal characteristics of the image signal. This is particularly important in medical image signals, where amplitudinal variations due to intrinsic and extrinsic imaging conditions can occur and post-processing techniques such as contrast enhancement are often performed. Given these advantages, the proposed method utilizes phase coherence characteristics obtained using complex-valued wavelets to adapt weights during the signal aggregation process.

The proposed method uses the robust iterative approach to complex wavelet phase coherence estimation [11] to extract the maximum moment of phase coherence $\gamma(x,y)$. An iterative phase-adaptive bilateral estimation scheme is used to improve the phase coherence estimate. The value of γ increases as perceptual importance for signal characteristics at a point increases. As such, high phase coherence coincide with important anatomical and functional characteristics within an image signal.

The weight assigned to information at point (x,y) from image signal f_i can then be determined based on a scaled exponential of the maximum moment of phase coherence:

$$w(x,y) = \alpha e^{\frac{\gamma(x,y)}{\beta}} \quad (4)$$

where α is the scaling coefficient, and β is a decay coefficient. Based on this formulation, higher weights are given to perceptually important signal characteristics such as important anatomical and functional characteristics within a medical image signal to accentuate such features in the fused image signal. Finally, the fused image signal can be computed using the following phase-adaptive weighted signal aggregation formulation:

$$g(x,y) = \frac{\sum_{i=1}^{n} \alpha e^{\frac{\gamma(x,y)}{\beta}} f_i(x,y)}{\sum_{i=1}^{n} \alpha e^{\frac{\gamma(x,y)}{\beta}}} \quad (5)$$

3 Experimental Results

The proposed fusion method was tested using three sets of medical image signals to evaluate its effectiveness at improving visualization of medical image signals. Each set consists of two image signals acquired using different imaging modalities. A summary of the test sets is given as follows:

1. **TEST 1**: T1-weighted MR and CT, Axial Cranial Slice, from Visible Human project.
2. **TEST 2**: T1-weighted MR and PET, Axial Cranial Slice, from Whole Brain Atlas [12].
3. **TEST 3**: T1-weighted MR and T2-weighted MR, Coronal Torso Slice, from Visible Human project.

The non-adaptive signal aggregation approach [2] is also performed for comparison purposes. Objective measures such as PSNR and MI are not suitable for evaluating multimodal image signal fusion since they do not reflect the human perception system. Therefore, a qualitative approach to evaluating image signal fusion should be used. The fused image signals produced using the proposed method are shown in Figures 1, 2, and 3. It can be seen that the important anatomical and functional characteristics from each of the image signals are noticeably accentuated in the proposed method compared to the non-adaptive signal aggregation approach [2], hence providing a clearer visualization of a patient's condition. For example, the bone structure characteristics captured by the CT signal in TEST 1 is noticeably clearer and prominent in the fused signal produced by the proposed method than that produced using non-adaptive signal aggregation. These experimental results demonstrate the effectiveness of the proposed method in improving visualization of medical image signals.

4 Conclusions

In this paper, we introduced a novel perceptual based approach to image signal fusion using complex-valued wavelets. By adapting the weighted aggregation process of the image signal fusion problem based on local phase characteristics, the fused image signal can be tuned to accentuate important anatomical and functional characteristics captured in the individual image signals. Experimental results show the effectiveness of the proposed method in improving the visualization of information content in images. Future work involves validating our results with clinicians and investigating alternative signal aggregation processes.

Acknowledgments

This research has been sponsored by the Natural Sciences and Engineering Research Council of Canada. The authors would also like to thank the National Library of Medicine for the Visual Human Project data and Dr. Keith Johnson from Massachusetts General Hospital.

References

[1] Z. Xue and R. Blum, "Concealed Weapon Detection using Color Image Fusion," *Proc. International Conference on Information Fusion*, vol. 1, pp. 622-627, 2003.

[2] Able Software Corporation. 3-D Doctor, Internet: http://www.ablesw.com/3d-doctor/index.html.

[3] R. Blum, "Robust image fusion using a statistical signal processing approach," *Information Fusion*, vol. 6, no. 2, pp. 119-128, 2005.

[4] G. Liu, Z. Jing, S. Sum, "Image fusion based on an expectation maximization algorithm," *Optical Engineering*, vol. 44, no. 7, 2005.

[5] Q. Guihong, Z. Dali, and Y. Pingfan, "Medical image fusion by wavelet transform modulus maxima," *Opt. Express*, vol. 9, pp. 184-190, 2001.

[6] S. Garg, K. Kiran, R. Mohan, and U. Tiwary, "Multilevel Medical Image Fusion using Segmented Image by Level Set Evolution with Region Competition," *IEEE EMBS*, pp. 7680-7683, 2001.

[7] A. Wong and W. Bishop, "Efficient Least Squares Fusion of MRI and CT Images Using a Phase Congruency Model," *Pattern Recognition Letters*, vol. 29, no. 3, pp. 173-180, 2008.

[8] M. Morrone and D. Burr, "Feature detection in human vision: A phase-dependent energy model," *Proc. the Royal Society of London B*, vol. 235, pp. 221-245, 1988.

[9] P. Kovesi, "Phase congruency detects corners and edges," *Proc. The Australian Pattern Recognition Society Conference*, pp. 309-318, 2003.

[10] Z. Wang and E. Simoncelli, "Local Phase Coherence and the Perception of Blur," *Advances in Neural Information Processing Systems*, vol. 16, 2004.

[11] A. Wong, "An iterative approach to improved local phase coherence estimation," *Proc. CRV*, 2008.

[12] Johnson, K., Becker, J. The Whole Brain Atlas. Internet: http://www.med.harvard.edu/AANLIB/home.html.

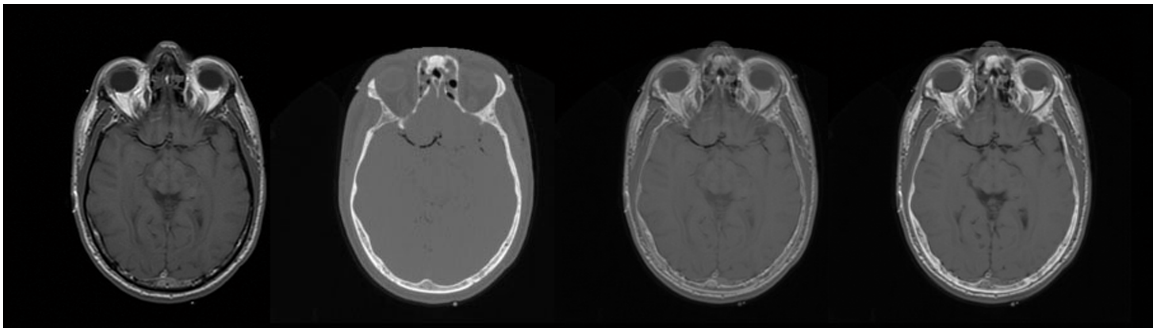

Figure 1. TEST 1: a) T1 MRI, b) CT, c) non-adaptive aggregation [2], d) proposed method

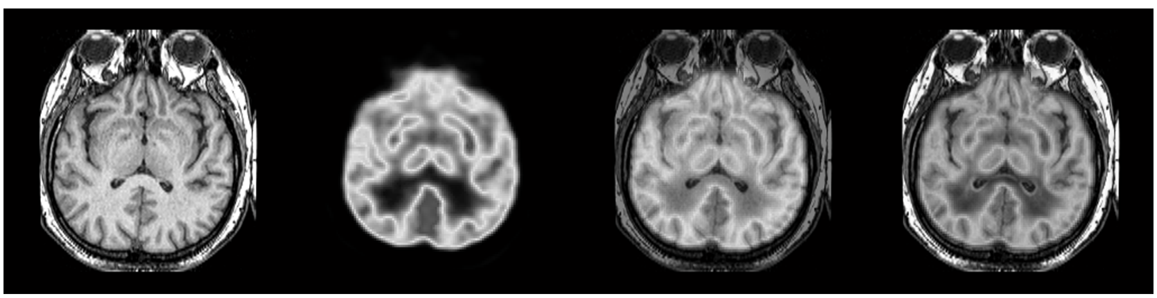

Figure 2. TEST 2: a) T1 MRI, b) PET, c) non-adaptive aggregation [2], d) proposed method

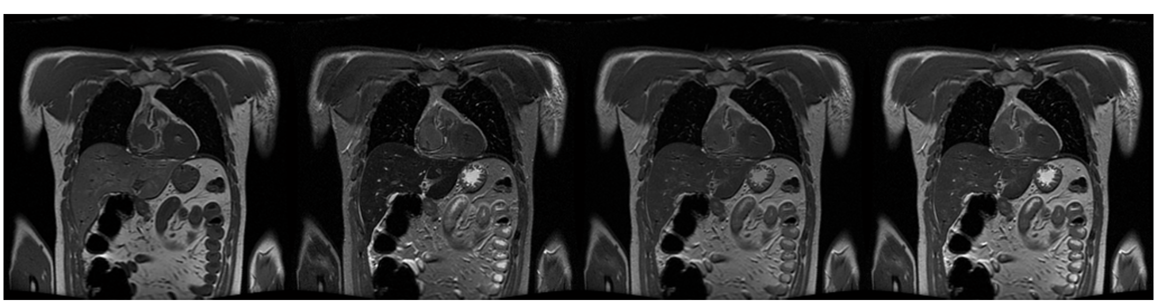

Figure 3. TEST 3: a) T1 MRI, b) T2 MRI, c) non-adaptive aggregation [2], d) proposed method