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# DE OPTIMIZED MEDICAL IMAGE FUSION USING MODIFIED SYNTHESIS BANKS OF DWT

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## ABSTRACT

In this paper, we focus on the fusion of images fromdifferent sources using multiresolution wavelet transforms with modified approach of analysis and filter banks. Based onreviews of popular image fusion techniques used in data analysis,different pixel and energy based methods are experimented. A novelarchitecture with a hybrid algorithm is proposed which applies pixelbased maximum selection rule to low frequency approximations andfilter mask based fusion to high frequency details of waveletdecomposition. The key feature of hybrid architecture is thecombination of advantages of pixel and region based fusion in asingle image which can help the development of sophisticatedalgorithms enhancing the edges and structural details. The quality of fusion is optimized using Differential evolution algorithm where filter banks optimization is performed to obtain a better visual experience from the fused images. A GraphicalUser Interface is developed for image fusion to make the researchoutcomes available to the end user. To utilize GUI capabilities formedical, industrial and commercial activities without MATLABinstallation, a standalone executable application is also developed using Matlab Compiler Runtime.

## I.INTRODUCTION

In recent years, there has been a growing interest in merging images obtained using multiple sensors in academia, industry, and military due to the important role it plays in the applications related to these fields. Image fusion, a class of data fusion, aims at combining two or more source images from the same scene into an image that retains the most important or salient features present in all the source images according to a specific fusion scheme. The composite image should provide increased interpretation capabilities and significantly reduce both human and machine errors in detection and object recognition. Moreover, image fusion can be performed at three different processing levels according to the stage where the fusion takes place: pixel, feature and decision level.

ITH rapid advancements in technology, it is nowpossible to obtain information from multisourceimages. However, all the physical and geometrical information required for detailed assessment might not beavailable by analyzing the images separately. In multisensoryimages, there is often a trade-off between spatial and

IJMTARC – VOLUME – V – ISSUE – 22, APR - JUNE, 2018

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spectralresolutions resulting in information loss. Image fusioncombines perfectly registered images from multiple sources toproduce a high quality fused image with spatial and spectralinformation. It integrates complementary information fromvarious modalities based on specific rules to give a bettervisual picture of a

scenario, suitable for processing. An imagecan be represented either by its original spatial representationor in frequency domain. By Heisenberg's uncertainty,information cannot be compact in both spatial and frequencydomains simultaneously. It motivates the use of wavelettransform which provides a multiresolution solution based ontime-scale analysis. Each subband is processed at a differentresolution, capturing localized time-frequency data of imageto provide unique directional information useful for imagerepresentation and feature extraction across different scales. Several approaches have been proposed for wavelet basedimage fusion which is either pixel or region based.

In pixel-level approach, all or a set of selected pixelsin the source images are combined to contribute to eachpixel in the fused image. Simple arithmetic rules or moresophisticated combination schemes can be applied to serve thispurpose. It is worth noting that the adopted merging procedureshould, in essence, contribute to a considerable performanceimprovement for all posterior processing tasks such as objectdetection and human/machine vision.

Feature extraction plays a major a role in the implementationof feature-level fusion approaches. Prior to the mergingof images, salient features, present in all source images, areextracted using an appropriate feature extraction procedure.Then, fusion is performed using these extracted features. Theextraction/detection stage should be optimal with respect toimage salient features and important regions.The most common of multi-resolution decompositionschemes for image fusion has been the wavelet transform.Particularly, wavelet-based image fusion algorithms using theDiscrete Wavelet Transform (DWT), Stationary WaveletTransform (SWT), and Dual Tree Complex WaveletTransform (DT-CWT) have been proposed. The advantageof the DT-CWT relative to the DWT and SWT lies in its addeddirectionality and its balance between overcompleteness andnear shift invariance. As a result, image fusion algorithmsusing the DT-CWT have been shown to be able to outperformthe other wavelet-based approaches.

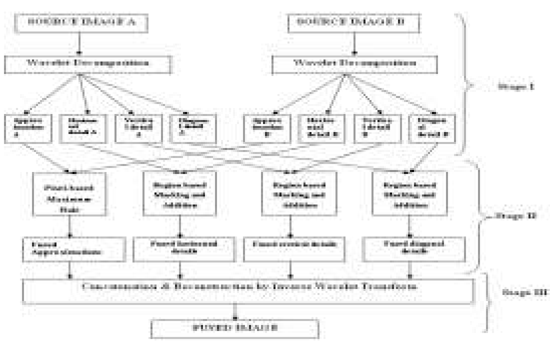
In order to represent salient features more clearly andenrich the information content in multisensory fusion, regionbased methods involving segmentation and energy basedfusion were introduced.Other fusion methods are based on saliency measurement,local gradient and edge fusion. Pixel basedalgorithms concentrate on increasing image contrast whereasregion based algorithms provide edge enhancement andfeature extraction. A few attempts have been madeto combine these algorithms in a single fused image. Theintegration of image fusion algorithms offers immensepotential

IJMTARC – VOLUME – V – ISSUE – 22, APR - JUNE, 2018

ISSN: 2320-1363

for future research as each rule emphasizes ondifferent characteristics of the source image. This paperproposes novel hybrid architecture (algorithm) for waveletbased image fusion combining the principles of pixel andregion based rules. To utilize the capabilities of image fusionat end user level, a Graphical User Interface is developed.There are several situations in which we would want to useapplications developed in MATLAB for commercial andresearch activities. A standalone executable has beendeveloped for the targeted image fusion application usingMatlab Compiler Runtime library.

## II.BLOCK DIAGRAM




The differential evolution algorithm is explained as follows.

A basic variant of the DE algorithm works by having a population of candidate solutions (called agents). These agents are moved around in the search-space by using simple mathematical formulae to combine the positions of existing agents from the population. If the new position of an agent is an improvement it is accepted and forms part of the population, otherwise the new position is simply discarded. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

Formally, let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be the cost function which must be minimized or fitness function which must be maximized. The function takes a candidate solution as argument in the form of a vector of real numbers and produces a real number as output which indicates the fitness of the given candidate solution. The gradient of $f$ is not known. The goal is to find a solution $m$ for which $f(m) \leq f(p)$ for all $p$ in the search-space, which would mean $m$ is the global minimum. Maximization can be performed by considering the function $h := -f$ instead.

Let $\mathbf{x} \in \mathbb{R}^n$ designate a candidate solution (agent) in the population. The basic DE algorithm can then be described as follows:

- Initialize all agents $\mathbf{x}$ with random positions in the search-space.
- Until a termination criterion is met (e.g. number of iterations performed, or adequate fitness reached), repeat the following:
  - For each agent $\mathbf{x}$ in the population do:
    - Pick three agents $\mathbf{a}, \mathbf{b}$, and $\mathbf{c}$ from the population at random, they must be distinct from each other as well as from agent $\mathbf{x}$
    - Pick a random index $R \in \{1, \ldots, n\}$ ($n$ bei

IJMTARC – VOLUME – V – ISSUE – 22, APR - JUNE, 2018

ISSN: 2320-1363

ng the dimensionality of the problem to be optimized).

- Compute the agent's potentially new position $\mathbf{y} = [y_1, \ldots, y_n]$ as follows:
  - For each $i$, pick a uniformly distributed number $r_i \equiv U(0,1)$
  - If $r_i < \mathrm{CR}$ or $i = R$ then set $y_i = a_i + F \times (b_i - c_i)$ otherwise set $y_i = x_i$
  - (In essence, the new position is outcome of binary crossover of agent $\mathbf{x}$ with intermediate agent $\mathbf{z} = \mathbf{a} + F \times (\mathbf{b} - \mathbf{c})$.)
- If $f(\mathbf{y}) < f(\mathbf{x})$ then replace the agent in the population with the improved candidate solution, that is, replace $\mathbf{x}$ with $\mathbf{y}$ in the population.
- Pick the agent from the population that has the highest fitness or lowest cost and return it as the best found candidate solution.

Note that $F \in [0,2]$ is called the *differential weight* and $\mathrm{CR} \in [0,1]$ is called the *crossover probability*, both these parameters are selectable by the practitioner along with the population size $\mathrm{NP} \geq 4$ see below.

## III.IMPLEMENTATION

### ALGORITHM:

The algorithm for hybrid fusion rule can be divided intothree different stages with reference to block diagram.

**Stage I**

1) Read the two source images A and B to be fused.

2) Perform independent wavelet decomposition of the twoimages until level L to get approximation $(LL^L)$ anddetail$(LH^l, HL^l, HH^l)$ coefficients for *l*=1,2,...,*L*.

**Stage II**

1) Select pixel based algorithm for approximations $(LL^L)$ which involves fusion based on taking the maximumvalued pixels from approximations of source images Aand B.

$$LL_f^L = \max imum(LL_A^L(i,j), LL_B^L(i,j))$$

Here, $LL_f^L$is the fused and $LL_A^L$ and $LL_B^L$ are the inputapproximations, *i* and *j* represent the pixel positions ofthe subimages.

2) A binary decision map is formulated based on themaximum valued pixels between the approximations. Thedecision rule $D_f$for fusion of approximation coefficientsin the two source images A and B is thus given by (5).

$$D_f(i,j) = 1, d_A(i,j) > d_B(i,j)$$
$$= 0, otherwise \qquad (5)$$

3) A small window of size 3X3 or 5X7 is selected from thedetail subbands based on whether the type of filter maskused is square or rectangular.

4) Perform region level fusion of details by applying 3X3square and 5X7 averaging filter mask to detailcoefficients. The

IJMTARC – VOLUME – V – ISSUE – 22, APR - JUNE, 2018

ISSN: 2320-1363

resultant coefficients are added fromeach subband.

$$LH_f^l = mask(LH_A^l) + mask(LH_B^l)$$

$$HL_f^l = mask(HL_A^l) + mask(HL_B^l)$$

$$HH_f^l = mask(HH_A^L) + mask(HH_B^L)$$

where

$LH_f^l$, $LH_A^l$, $LH_B^l$ are vertical high frequencies,

$HL_f^l$, $HL_A^l$, $HL_B^l$ are horizontal high frequencies,

$HH_f^l$, $HH_A^L$, $HH_B^L$ are diagonal high frequencies

**Stage III**

1) We obtain the final fused transform $LL_f^L$ correspondingto approximations through pixel rules and the vertical,horizontal and diagonal details $LH_f^l, HL_f^l, HH_f^l$ bymask based fusion where $l$=1,2,...,$L$.

2) The new coefficient matrix is obtained by concatenatingfused approximations and details.

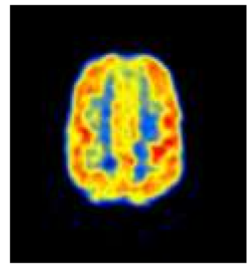
3) Fused image is reconstructed using inverse wavelettransform and displayed.

## IV.OUTPUTS

Original first image

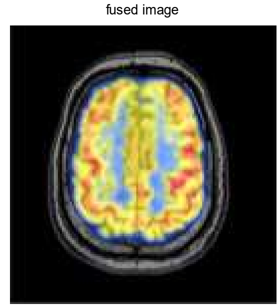
ORIGINAL SECOND IMAGE

Original second image



FUSED IMAGE

fused image



Original first image

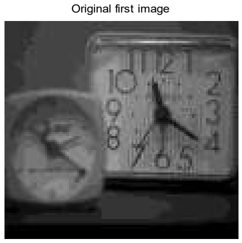
IJMTARC – VOLUME – V – ISSUE – 22, APR - JUNE, 2018

ISSN: 2320-1363

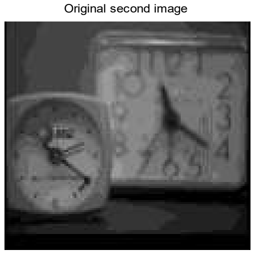
Original second image

fused image

Original first image



Original second image



fused image

## V.CONCLUSION

The work done in this project forms the basis for furtherresearch in wavelet based fusion and other methods whichintegrate the fusion algorithms in a single image. The basic difference between the existing and the proposed algorithm is, to work on the optimization of DE algorithm. The novelhybrid architecture presented here gives promising results inall test cases and can be further extended to all types ofimages by using different averaging, high-pass and low-passfilter masks. The variations in performance of fusion rules fordifferent test images show that the choice of an optimumfusion rule depends mainly on the type of images to be fused,degradation models used to introduce noise in source imagesand the application. Studies about the type of source imagenoises will pave way for developing intelligent image fusiontechniques capable of choosing the best rule depending on thetype of degradation models used in images.

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IJMTARC – VOLUME – V – ISSUE – 22, APR - JUNE, 2018
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