

# Accurate Registration for Low Resolution Images using Wavelet Neural Networks: A Novel Approach

Liyakathunisa, C.N. Ravi Kumar

**Abstract**—Accurate registration of multiple low resolution images is of central importance in many advanced image processing applications, since capturing of multiple low-resolution images taken of the same scene results in a distortion between each image. Image super-resolution is a typical application where the quality of the super-resolved image is degraded as registration errors increase. In this paper, we have proposed a Wavelet Neural Network (WNN) based image registration, where we are estimating the relative rotation, translation and shift between the observed images and the reference image. We are able to obtain an accurate registration which is very much essential for super resolution image reconstruction. Experimental results shows that the proposed approach is superior when compared to Fourier based registration. Fourier based registration works only for clean images, i.e. images without any degradation, where as our proposed WNN based registration works for severally, degraded images viz. blur and noise.

**Index Terms**— Accurate Registration, Low Resolution, Neural Network, Super Resolution, Wavelets.

## 1. INTRODUCTION

MOST Super Resolution algorithms can be decomposed into two parts: an image registration part followed by a reconstruction part. Very high accuracy is required in the image registration to be able to reconstruct the high resolution image correctly. Once the images are registered a robust reconstruction method is needed to build a high resolution image from the set of irregularly spaced low resolution images. Image registration is a typical application where the quality of the super resolved image is degraded as registration errors increase.

Super Resolution is a process of producing a high spatial resolution image from one or more Low Resolution (LR) observation. It includes an alias free up sampling of the image thereby increasing the maximum spatial frequency and removing the degradations that arises during the image capture. Viz Blur and noise [1][2]. It is the ability to use multiple noisy and blurred images obtained by low resolution cameras and together generating a higher resolution image with greater details than those you could get with just a single image.

The remainder of the paper is organized as follows. Section II, presents the Super Resolution Reconstruction (SRR) problem formulation; In Section III we discuss about Image Registration, in section IV the proposed registration for Super resolution Reconstruction. Section V provides the simulation results and, finally in section VI consists of conclusion.

## 2. SUPER RESOLUTION RECONSTRUCTION PROBLEM FORMULATION

When multiple images obtained from different sensors, different viewpoints, or at different times are taken of the same scene, they become distorted with respect to each other [2]. The problem arises when knowledge of this displacement is unknown. Image registration aims to find the optimal transformation matrix that transforms the distorted image, known as an input image, back into spatial alignment with a reference image.

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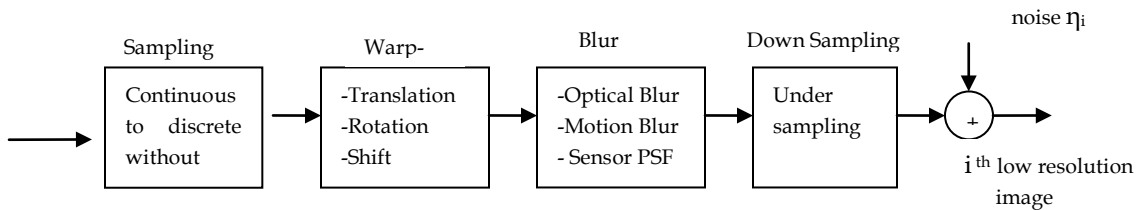


Figure 1: Super Resolution observation Model

The problem is formally described as

$$g_i = DB_i W_i f[x_i] + n_i \quad \text{where } i=1 \dots h \quad (1)$$

Where

- $f$  - is the unknown high resolution
- $g_i$  - is the  $i$  th low resolution image
- $D_i$  - is the down Sampling operator
- $W_i$  - represents warping,
- $B_i$  - represents Blur and
- $n_i$  - represents the noise.

The super resolution observation model is show in fig 1, a real world scene is observed, wraped at the camera lens due to the relative motion between the scene and the camera. The images are often degraded by both optical and motion blur. They are discretized or down sampled resulting in an aliased, blurred and noisy low resolution image. The objective is to obtain a high resolution image from a set of low resolution images.

### 3. IMAGE REGISTRATION FOR SUPER RESOLUTION RECONSTRUCTION

Image Registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or different sensors. It geometrically aligns two images -the reference and the sensed image. Typically image registration is required in remote sensing application such as change detection, multispectral classification, environmental monitoring, image mosaicing, medical image reconstruction and super resolution reconstruction [3]. In general, majority of automated registration methods consist of the following four steps: Feature extraction, feature matching, transform modeling and image resampling [3]. In feature Extraction step, manually or preferably automatically, salient and distinct features are extracted. In feature matching step, the correspondence between the features detected in the sensed image and those detected in the reference image is established. In the transform modeling step, the parameters of the mapping function are computed by means of the established feature correspondence.

Finally in image resampling step, the sensed image is registered by means of the mapping function. A detail Survey of image registration techniques is discussed in [3] [4]. Image registration algorithms can further be classified into spatial domain and frequency domain methods. Spatial domain methods operate using features, structures and textures as matching criteria. Some of the feature matching algorithms are out growth of the traditional techniques for performing manual image matching in which operators choose matching control points (CPs) between images. When the number of control points exceeds the minimum required to define the appropriate transformation model iterative algorithms like RANSAC are used to robustly estimate the best solution. Frequency domain methods use the properties of Fourier Transforms (FT).

### 4. PROPOSED REGISTRATION FOR SUPER RESOLUTION RECONSTRUCTION.

In Super Resolution Reconstruction the first preprocessing task of utmost importance is accurate registration of the acquired images. In image registration typically one image called the base image is considered the reference, to which the other images called input images are compared. The objective is to bring the input image in alignment with the base image by applying a spatial transformation to the input image. Spatial transformations maps locations in one image into a new location in another image. Image registration is an inverse problem as it tries to estimate from sampled low resolution images  $g_i$ , the transformation that occurred between the views  $[g]$  and  $f[x_i]$  considering the observation model of Eq(1). It is also dependent on the properties of the camera used for image acquisition like sampling rate (or resolution) of sensor, the imperfection of the lens that adds blur, and the noise of the device. As the resolution decreases, the local two dimensional structure of an image degrades and an exact registration of two low resolution images becomes increasingly difficult. Super resolution reconstruction requires a registration of high quality.

We first investigated the Fourier based registration as proposed by [5][6][7][8][9]. Fourier-based algorithms use the properties of the Fourier transform to register images. Shifts, rotations, scales, and other transformations can be represented in a compact, easily interpreted way in the Fourier domain. The general approach of Fourier techniques is to use phase correlation, which exploits the translation property of the Fourier transform. If an input image is shifted when compared to a reference image, the only difference will be a phase difference, which can be used to determine the shift difference between the two images. Rotation is approximated in the same manner as translation, with the preprocessing step of changing the Cartesian coordinates to polar coordinates [7].

The Fourier method is relatively fast when using the Fast Fourier Transform (FFT). Another nice property of Fourier-based techniques is that they perform well, even with the addition of correlated and frequency-dependent noise. However, this technique fails with the addition of white noise and blurs [7]. The shortcomings of Fourier techniques can be overcome by our proposed Wavelet Neural Network approach for registration of LR images.

Wavelet transforms decomposes a signal into a set of basis functions unlike Fourier transforms, whose basis functions are sinusoids, wavelet transforms are based on small waves called wavelets of varying frequency and limited duration. A detailed discussion about wavelets is presented in our earlier work [1]. In wavelet decomposition of an image, we obtain one approximate (LL) and three detail (LH, HL and HH) sub-bands.

The network architecture and the signal processes used to model nervous system can roughly be divided into three categories, each based on different philosophy. A feed forward network [17] transforms sets of input signal into sets of output signals. The desired input-output transformation is usually determined by external supervised adjustment of the system parameters. In feed back networks [17], the input information defines the initial activity state of a feed back system, and after state transition the asymptotic final state is identified as the outcome of the computation. In the third category, neighboring cells in a neural network compete in their activities by means of mutual lateral interaction, and develop adaptively into specific detectors of different signal patterns. In this category learning is called competitive, unsupervised or self organizing map [17]. In unsupervised learning the system is supposed to discover statistically salient features of the input image. Unlike supervised learning, there is no a priori set of categories into which the patterns are to be classified; rather the system must develop its own representation of the input stimuli. We have considered feed forward network for estimating the angle of rotation, translation and shift.

We have proposed Wavelet Neural Network based registration to accurately register low resolution images. Wavelets have several nice properties that make them well suited for image registration. Multiple scales of the wavelet transform can be used, which allows better registration accuracy because several scales can be utilized to create a more accurate prediction. Wavelet transform produces decomposition at several levels or scales refers to the property of multiresolution. Another significant property of wavelet transform is compression; it reduces the amount of significant information to small amount.

#### 4.1 PROPOSED ALGORITHM

WNN based registration consists of two phases. The training phase and the testing phase.

##### *Training Phase:*

In this phase, a training set of 200 low resolution images, each translated and rotated by random angle from the reference image were simulated. Additive white Gaussian noise and blur was added. Each training set images were decomposed using Discrete Wavelet Transform (DWT) upto level five. The LL coefficients were extracted which consisted of 64 LL coefficients. Hence the feed forward neural network consists of 64 input neurons, 40 hidden layers and 4 outputs (Tx, Ty, R, S). The LL coefficients were trained using BP algorithm. The back propagation algorithm consists of feed forward, back propagation of error and updation of weights. During feed forward each input unit receives an input signal and transmits this signal to each of the hidden units. Each hidden unit calculates the activation function and sends its signal to output unit. The output unit calculates the activation function to form the response of the net for the given input parameters.

During Back propagation of errors, each output unit compares its computed activation output with its target output, to determine the associated error for that parameter. Based on the error, the factor  $\delta_k$  is computed and is used to distribute the error at output unit  $o_k$  back to all units in previous layer. Similarly, the factor  $\delta_j$  is computed for each hidden unit  $w_{jk}$ , the weights are updated using the factor  $\delta$  and the activation function. Sigmoid transfer functions were deployed from hidden layer to the output neurons, while linear function characterizes from input to the hidden neurons. The network was trained using gradient descent learning algorithm, to obtain the angle of rotation, translation and scale parameters. Figure 2, depicts the Training Phase.

Algorithm 1: Wavelet- Neural Network based Training Phase for estimating the angle of rotation, scale and translation

Input :

I: Input Reference Image

Target Output:

$$tk = \{Tx, Ty, R, S\}$$

Actual Output:

$$Ok = \{Tx, Ty, R, S\}$$

which is actual neural network output obtained when Input Vector I if fed to the NN.

Steps:

Step 1: Create a training set of low resolution images.

Step 2: Apply DWT to the low resolution images.

Step 3: Extract LL coefficients from the DWT decomposed images.

$$\{LL_1, LL_2, LL_3, \dots, LL_n\}$$

Step 4: Repeat Steps 4 to 14, for each image in the training set.

Step 5: Feed the Extracted LL DWT co-efficient to neural net input neurons.

Step 6: Each input unit receives the input signal and transmits this signal to all units in the layer above i.e. hidden units.

Step 7: Each hidden unit sums its weighted input signal

$$net_i = \sum_j w_{ij} o_j$$

by applying the linear activation function

Step 8: Each output unit sums its weighted input Signal by applying the sigmoid activation Function

$$net_k = \sum_j w_{jk} o_j$$

by applying the sigmoid activation function

Step 9: At the obtain layer, we obtain translation  $T_x$  , translation  $T_y$  , rotation R and Scale S.

$$O_k = \{T_x, T_y, R, S\}$$

Step 10: Calculate the error of the output nodes between target and actual Output  $(t_k - o_k)$

$$\delta_k = (t_k - o_k) * f'(net_k)$$

Step 11: Calculate the error of the hidden nodes (based on the error of the output nodes it is back propagated to the hidden nodes)

$$\delta_j = \delta_k * w_{jk}$$

Where  $\delta_k$  is error at corresponding output neuron,  $w_{jk}$  is weight across the hidden layer neuron.

Step 12: Update weights using standard delta rule with the appropriate error Function  $\delta$  .

Step 13: Each output unit updates its weight, the weight correction is given by

$$\Delta w_{jk} = \alpha * \delta_k * O_j$$

Where  $\alpha$  is the learning rate.

Therefore,

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk}$$

Step 14: Each hidden unit updates its weight; the weight correction is given by

$$\Delta w_{ij} = \alpha * \delta_j * O_i$$

Therefore,

$$w_{ij}(new) = w_{ij}(old) + \Delta w_{ij}$$

Step 15: Test for the Stopping condition.

The stopping condition is the number of epochs.

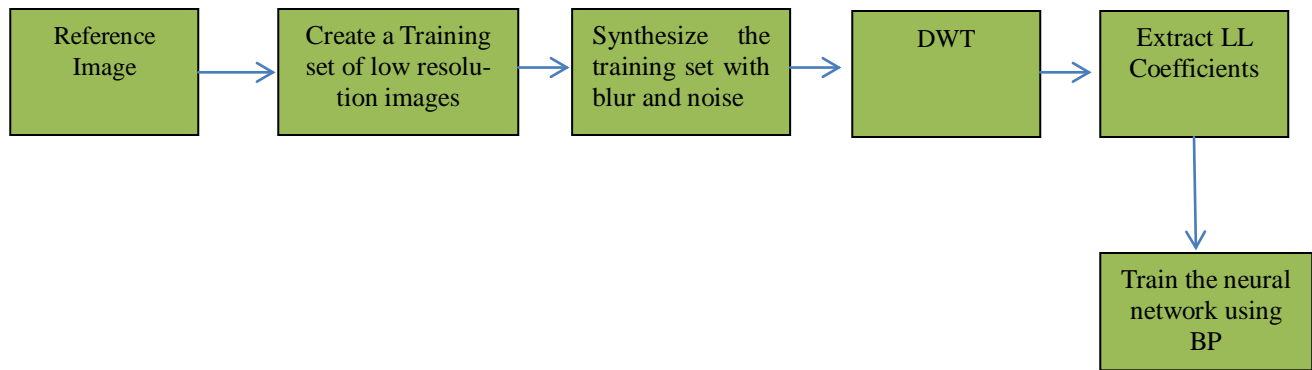


Fig 2: Wavelet-Neural Network based Training Phase for Image Registration

**Testing Phase:**

The Block diagram of the Testing Phase in illustrated in Figure 3. In this phase an input rotated and shifted, low resolution image is decomposed using discrete wavelet transform to obtain LL, LH, HL and HH coefficients. The LL coefficients are extracted and feed to the neural network, which is trained using error BP algorithm. The output of the network is the four parameters translation Tx in horizontal direction, translation Ty in vertical direction, angle of rotation and scale of the input image. Once the angle of rotation and translation are estimated from the neural network, reverse transforms are applied to get the accurately registered image.

Algorithm 2: Wavelet-Neural Network Based Testing Phase for Estimating the Angle of Rotation, Scale and Translation

Input :  $I = \{LL\}$  consists of LL DWT co-efficient

Output: Registered Image

$$O = \{T_x, T_y, R, S\}$$

**Steps:**

- Step 1: Apply DWT on Input Low resolution image and Extract the LL Co-efficient.
- Step 2: The Extracted LL co-efficient are fed to input layer neurons of a trained Neural Network.
- Step 3: The output of the network is a normalized vector consisting of registration parameters

$$O = \{T_x, T_y, R, S\}$$

Where Tx, Ty are Translation in horizontal and a vertical direction, R is Rotation, and S is Scale.

- Step 4: Apply the reverse rotation and shift to get the registered image.

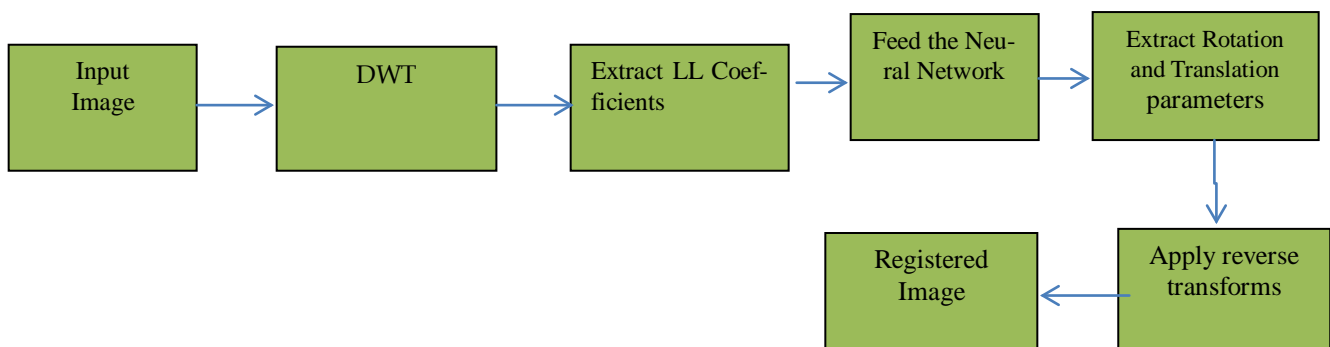


Fig 3: Wavelet-Neural Network based Testing Phase for Image Registration

## 5. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, we address the performance of our proposed approach in terms of accurate registration for translated, rotated, blurred, noisy and aliased low resolution images.

The performance of the registration algorithm developed is tested on different sets of images. Different amounts of noise and blur are also added to test the algorithm's robustness against noise and blur. Tests were performed on both simulated and real world images. In the test of simulated images a new image was made by shifting an original (Reference) image by certain number of columns and rows, and by rotating with a certain angle.

The following two cases, shown in Figure 4 and Figure 5 were used in the simulations, Case 1 is a low resolution Lena image, Figure 4(a) is the original (reference) image, Figure 4(b) is the simulated image obtained from the original by a rotation of 30 degrees and a shift of 3 columns (pixels) by 3 rows (pixels).

The results of applying the Wavelet- Neural Network based registration is shown in Figure 4(c). The resultant image of Figure 4(c) is almost exactly the same as the reference image. Similar tests were performed on Brain MRI image, shown in Figure 5.

It is clearly evident from the Table 1 that the performance of our algorithm is various scales, translation and rotation and also in the presence of noise and blur is very efficient. Therefore, if an image has translations, rotations and scale changes, our algorithm ought to remove the translation or rotation, despite the difference in scale. Another significant advantage of our algorithm is that it registers accurately severely degraded blurred and noisy low resolution images. As wavelet decomposition of an image filters the noise and smoothens the image, which is very essential for a precise registration. To the best of our knowledge, we have pioneered this concept of removing the noise and blur reasonably while registration which is the inherent characteristics of the process employed.

### Case 1: Lena Image

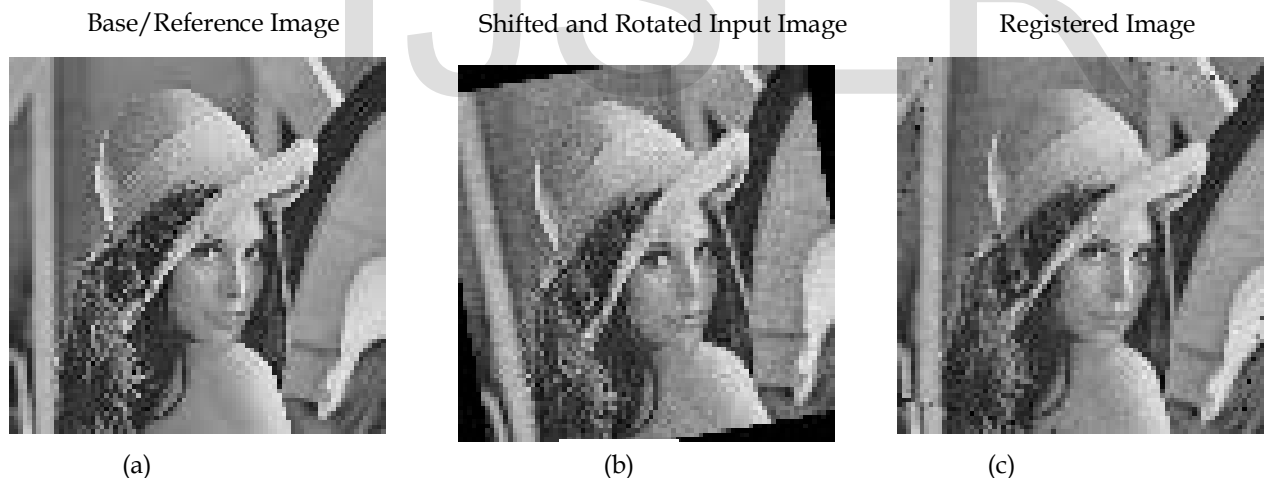


Fig 4: Lena Image: (a) Reference image (b) shifted rotated image (c) Registered image

**Case2: Brain MRI Image**



Fig 5: Lena Image: (a) Reference image (b) shifted rotated image (c) Registered image

Table 1: Results of Translated (Shift), Rotated Images using WNN based Registration

Source Image	Original Image			Estimated Image		
	Translation in X (pixels)	Translation in Y(pixels)	Rotation (degrees)	Translation in X (pixels)	Translation in Y(pixels)	Rotation (degrees)
Lena	5	5	20	5	5	19.89
Brain MRI	4	4	20	4	4	19.84

**5. CONCLUSION**

In Super resolution reconstruction during the image capture, the images are rotated, shifted, translated, blurred, noisy and sub pixel shifted which results in low resolution images. If the images are sub pixel shifted due to rotation, translation and shift, then perfect super resolution is impossible for reconstruction. Hence to reconstruct a high resolution image perfect registration is of utmost importance. We have proposed a WNN based registration, which estimates the exact rotation, shift and translation parameters, which are used for an accurate registration of a Super Resolution Reconstruction of low resolution images.

our proposed wavelet-neural network based registration include, fast neural computation, less computational complexity due to the less number of neurons used, and convergence problem and lengthy training algorithm are not needed. In addition the proposed algorithm takes less time to process and accurately register the low resolution images, compared to other spatial and frequency domain approaches. The proposed method accurately registers images at various scales, translations, and rotations in the presence of noise, blur and aliasing. Therefore, if an image has translations, rotations and scale changes, our algorithm ought to remove the translation or rotation, despite the difference in scale. From the experimental results it is evident that our methods are superior to other approaches.

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