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Original Article

Hybrid Multi-Scale Feature Transform Based Fusion of X-Ray and Radar Image

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Abstract *- X-ray and radar imaging are two different imaging techniques that can be used for various applications, such as security screening, medical imaging, and geophysical exploration. High-energy X-rays are used to make images of objects by detecting their backscattered radiation. The generated image contains information on the object's interior structure and composition. Instead, radar imaging employs radio waves to form images by measuring reflected signals' time delay and intensity. X-ray and radar images are aligned using a feature-based registration method. The goal of feature-based registration is to find corresponding points or features in the pictures and use them to compute the transformation that aligns the images. This paper proposed a Multi-Scale Feature Transform (MSFT) to improve the performance of feature extraction and object recognition tasks. Experimental results using image quality tests demonstrate that Multi-scale transform fusion performs better based on lesser false data, higher colour accuracy, and better image visibility.*

Keywords *- Multi-Scale Feature Transform, Feature-based registration, Fusion image, X-Ray and radar image, NDT.*

1. Introduction

X-ray backscatter imaging is a technique used in radiography to generate images by measuring the backscattered X-ray radiation from an object or material. Unlike traditional X-ray imaging that relies on transmitted X-rays, backscatter imaging utilizes X-rays scattered or reflected from the examined object. The basic principle of X-ray backscatter imaging involves directing a focused X-ray beam towards the object of interest and detecting the scattered X-rays [1]. The intensity and energy distribution of the backscattered X-rays are measured, and an image is formed based on this information.

X-ray backscatter imaging offers several advantages in specific applications. It can provide information about objects' internal structure and composition, including hidden objects or materials concealed within other substances. This technique is often used for security screening at airports and other high-security locations to detect concealed weapons, drugs, or contraband. It can also be applied in Non-Destructive Testing (NDT) to inspect and analyze the integrity of structures, materials, or manufactured components [2]. Holographic radar imaging is a technique that combines holography and radar principles to generate high-resolution images of objects or scenes. It can obtain detailed information about targets' shape, position, and movement, even in challenging environments such as through walls, foliage, or adverse weather conditions [3]. Holographic radar imaging offers several advantages compared to traditional radar imaging techniques. It provides high-resolution imaging capabilities, allowing for detailed analysis of complex scenes [4].

X-ray backscatter imaging and holographic radar are two distinct imaging techniques used in different applications and operating principles [5]. X-ray backscatter and radar imaging are other imaging techniques that can be used for various applications, such as security screening, medical imaging, and geophysical exploration [6]. It can also penetrate through certain materials or obstacles that may impede other imaging methods. Holographic radar imaging finds applications in various fields, including aerospace, defence, surveillance, remote sensing, and environmental monitoring. The specific implementation of holographic radar imaging systems may vary depending on the radar technology, signal processing techniques, and computational algorithms. The advancement of holographic radar imaging continues to be an active area of research, aiming to improve imaging quality, resolution, and system performance [7, 8].

X-ray backscatter imaging involves using high-energy X-rays to create images of objects by measuring the backscattered radiation produced when the X-rays interact with the thing. The resulting image provides information about the object's internal structure and composition [9]. Radar imaging, on the other hand, uses radio waves to create images of objects by measuring the time delay and strength of the reflected signals. The resulting image provides information about the object's shape and position. Combining the two imaging techniques can provide a more comprehensive and accurate picture of the object being imaged [10]. For example, combining X-ray backscatter imaging with radar imaging in security screening applications can help detect concealed weapons or explosives that might be missed by either technique alone.

The existing literature can be critically reviewed to identify research gaps in feature transform-based fusion of X-ray and radar images. Basic fusion methods and traditional algorithms may be the focus of many studies. Developing more advanced and effective feature transformation techniques tailored explicitly for X-ray and radar image fusion could be lacking. Modality, data acquisition, and characteristics of X-ray and radar images differ significantly. Medical imaging, remote sensing, or security applications may require more research into domain-specific feature transformation methods for X-ray and radar image fusion. In contrast to previous research, this study combines multiple transformation techniques to exploit their complementary strengths rather than focusing on a single type of feature transformation (e.g., wavelet, Fourier, or CNN-based features).

2. Related Works

In medical applications, separated format images fail to provide appropriate information for diagnosis. As a result, it is essential to integrate the benefits, or complementarities, of several image modalities. This research [11] offered an effective method for the fusion of medical images using the distinct wavelet transform and an optimization approach called inverse crow searching. This paper [12] presents a unique proposal for a synchronously adaptable framework for the fusion of multi-band images, which is based on integrated methodologies that are model and data-driven. The neural kernels in the initial level of the above technique's large stacking neural network with convolution for images were given an updated definition after applying Gaussian and Gaussian-Laplace filtering. This allowed the approach to be used for multi-band images.

The noise from speckles dramatically affects the image clarity by diminishing the image's features, such as edge details, reducing the contrast, and causing resolution difficulties. To cut down on the speckle noise, researchers have looked at a few different avenues of inquiry [13-15]. In computer vision, 'image reconstructions' refers to low-level vision tasks that restore and convert damaged images into excellent-quality images. Image reconstruction is used in medical imaging to get higher-quality images for therapeutic applications at a reduced cost and danger to patients [16]. This is accomplished via the utilization of image reconstruction. The Generative Adversarial Network, more often called GAN, is a relatively new advancement area in deep learning. Suppose these many forms of networks start cooperating and stop trying to one-up one another and instead start cooperating to maintain arm-in-arm links to one another's worlds. In that case, the results will be different [17]. This article [18] covers a method in X-ray absorption measurement taken across the head at several different angles. The absorbance coefficients of the material present within the skull are estimated on a machine employing these data; then, the results are shown as a sequence of photos of segments from the forehead. This research [19] gives an in-depth status report on the various computational compression approaches currently used for medical imaging data. This article looks at the appropriate categorization, performance measures, practical concerns, and challenges in improving two-dimensional and three-dimensional medical image compression.

In the recent past, the field of computer vision has seen significant development and undergone a revolutionary change from human-engineered features to automated ones to solve complex tasks. Whenever a discovery leads to a more intuitive understanding and operation of the visual system in humans, it will often cause a change in the strategy used to create algorithms for computer vision [20]. The area of computer vision is constantly developing and may trace its roots back to the discipline of neurology. In theory, recurrent networks can retain previous inputs and use them to generate the output that is now being sought. As a result of this quality [21], recurrent networks help predict time series and control processes.

This article [22] discusses the effects that deep learning technologies have had on the design of cameras. A camera's primary job is to take images, but its secondary job is to build an image from the data it has taken. Deep learning helps enhance the merging of images from many apertures to allow task-specific array cameras when applied to lens design. The living body comprises an infinite number of intricate and complicated structures, and even though these structures have been researched in the past, a significant quantity of knowledge relevant to them is still unidentified. This article [23] contains a discussion of the recent developments in technical and analytical fields.

3. Proposed Methodology

X-ray backscatter imaging involves using high-energy X-rays to create images of objects by measuring the backscattered radiation produced when the X-rays interact with the thing. The resulting image provides information about the object's internal structure and composition. Radar imaging, on the other hand, uses radio waves to create images of objects by measuring the time delay and strength of the reflected signals. In our proposed model, the Feature-based registration method used for image registration is a process that aligns two or more images of the same scene taken from different viewpoints, time points, or imaging modalities. Let's explore each method in more detail: Feature-based registration involves identifying and matching distinctive image features to establish correspondences. These features can be points, edges, corners, or other identifiable structures. The registration process involves the following steps:

- Feature Detection : Features are identified in each image using corner detection, Scale-Invariant Feature Transform (SIFT), or Speeded-Up Robust Features (SURF). These algorithms locate key points in the image that are likely to be unique and repeatable.
- Feature Description : Descriptors are computed for each detected feature to capture its distinctive characteristics. These descriptors encode information about the local image patch around the feature point.
- Feature Matching : Corresponding features between the images are determined by comparing the descriptors. Various techniques such as nearest neighbour matching, Random Sample Consensus (RANSAC), or geometric constraints can be employed to establish accurate correspondences.
- Transformation Estimation : Once feature correspondences are established, a geometric transformation (e.g., affine or projective) can be estimated based on the matched features. This transformation is used to align the images.

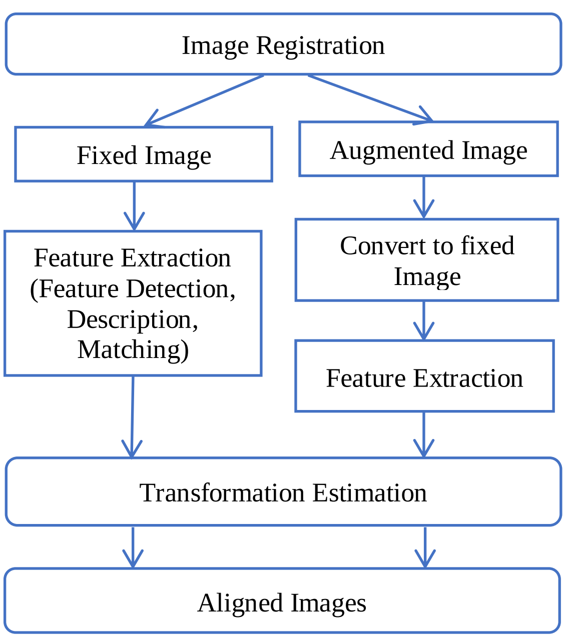


Fig. 1 Procedure of image registration

Feature-based registration is robust to image intensity, contrast, and noise differences. It is beneficial when dealing with non-rigid deformations or images acquired under different conditions.

However, it relies on the images' availability of distinct and reliable features. The overall architecture of the proposed model is shown in Figure 2. The resulting image provides information about the object's shape and position. Combining the two imaging techniques can provide a more comprehensive and accurate picture.

3.1. Multi-Scale Feature Transform

Multi-Scale Feature Transform (MSFT) is a computer vision technique that aims to improve the performance of feature extraction and object recognition tasks. MSFT is based on the idea that objects in images can have different sizes and resolutions, and therefore, features extracted at different scales can provide complementary information. MSFT achieves this by applying multiple filters with varying heights to the input image and concatenating their outputs to create a multi-scale feature map.

The MSFT approach has been utilized in computer vision applications, such as object detection, segmentation, and image classification. One notable application of MSFT is in the YOLOv4 object detection algorithm, which uses a spatial pyramid pooling module based on MSFT to capture features at different scales. The Multi-Scale Feature Transform (MSFT) algorithm may be classified into the following steps:

Input image: The MSFT algorithm takes an input image as its input.

Scale selection: The algorithm selects multiple scales for feature extraction. This can be done using techniques such as Gaussian pyramids or image rescaling.

Feature extraction: The algorithm applies convolutional filters of different sizes to the input image at each selected scale to extract features. These features are then concatenated to create a multi-scale feature map.

Pooling: The multi-scale feature map is then processed using a pooling operation to aggregate features at each scale. The pooling operation can be performed using various techniques, such as max or average.

Output: The resulting multi-scale feature vector is then used for object recognition or other computer vision tasks. In summary, MSFT is a technique that leverages multi-scale information to improve feature extraction and object recognition performance in computer vision tasks.

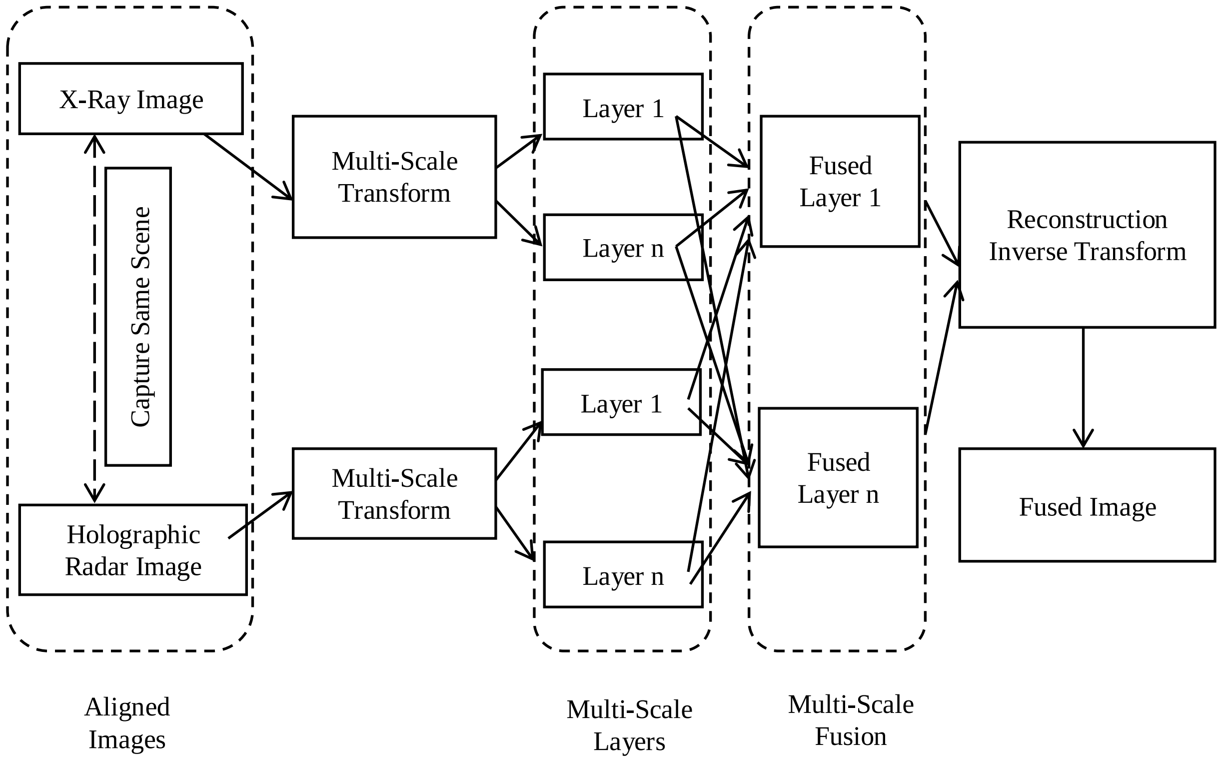


Fig. 2 Overall architecture of proposed system

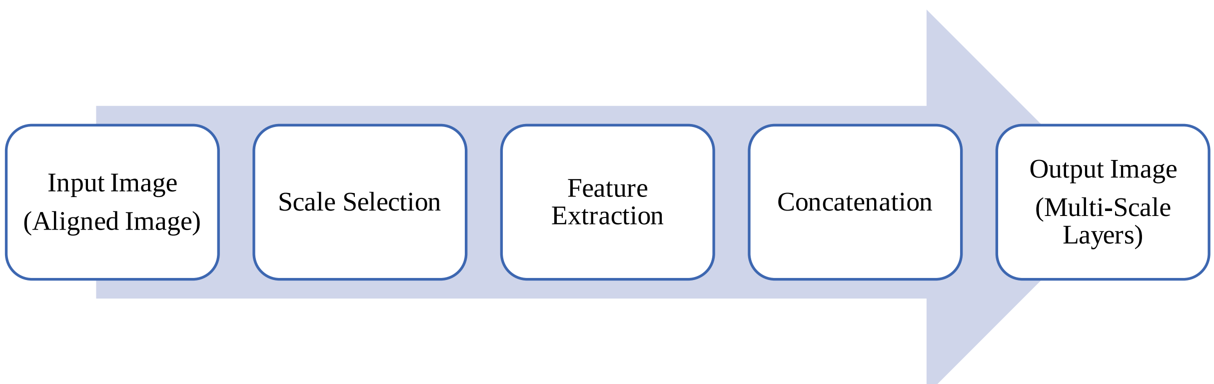


Fig. 3 Steps involved in MSFT

In Figure 3, the input image is first processed by selecting multiple scales to extract features using convolutional filters. The resulting segments are then concatenated to create a multi-scale feature map, which is processed using a pooling operation. The productivity of the pooling operation is a multi-scale feature vector that can be used for object recognition or other computer vision tasks.

3.1.1. Pseudocode for MSFT

```
function MSFT(xray_image, radar_image):
  pyramid1 = constructImagePyramid(xray_image)
  pyramid2 = constructImagePyramid(radar_image)
    for scale_level = pyramid1.numLevels to 1 do:
    current_ xray_image =
pyramid1.getImageAtLevel(scale_level)
    current_ radar_image =
pyramid2.getImageAtLevel(scale_level)
        features1 = detectFeatures(current_ xray_image)
    features2 = detectFeatures(current_ radar_image)
        matches = matchFeatures(features1, features2)
        transformation = estimateTransformation(matches)
        if scale_level > 1:
      upscale transformation to the next level
      return transformation
function constructImagePyramid(image):
  pyramid = empty Pyramid()
  pyramid.addImage(image)
  current_image = image
```

```
while current_image.width > min_width and
current_image.height > min_height:
        current_image = downsample(current_image)
        pyramid.addImage(current_image)
      return pyramid
function detectFeatures(image):    // Perform feature
detection using a specific algorithm
    features = featureDetectionAlgorithm(image)
    return features
function matchFeatures(features1, features2):    // Perform
feature matching using a specific algorithm
    matches = featureMatchingAlgorithm(features1, features2)
    return matches
function estimateTransformation(matches):    // Perform
transformation estimation using a specific algorithm
    transformation =
transformationEstimationAlgorithm(matches)
    return transformation
function downsample(image):    // Perform image
downsampling to reduce resolution
    downsampled_image = resize(image, scale_factor)
    return downsampled_image
```

3.2. Multi-Scale Fusion

Multi-scale fusion combines information from multiple scales or levels of an image pyramid to generate a fused output.

3.2.1. Pseudocode of Multi-Scale Fusion Algorithm

```
function MultiScaleFusion(image_pyramid):
    num_levels = image_pyramid.numLevels
    fused_image = createEmptyImage()
        for scale_level = 1 to num_levels do:
        current_image =
image_pyramid.getImageAtLevel(scale_level)
        fused_image = fuseImages(fused_image,
current_image)
     return fused_image
function fuseImages(xray_image, radar_image):
    // Perform fusion of two images using a specific algorithm
    fused_image = imageFusionAlgorithm(xray_image,
radar_image)
    return fused_image
```

The pseudocode assumes the existence of an image pyramid, which contains images at different scales or resolutions. The MultiScaleFusion function iterates over the image pyramid levels, starting from the lowest resolution, and fuses each level's image with the previously fused result. The fused image is updated and passed to the next level until all levels are processed. The final fused image is then returned.

The fuseImages function represents the specific fusion algorithm used to combine two images. The details of this algorithm will depend on the requirements and techniques employed in the fusion process. It could involve blending, weighted averaging, wavelet transforms, or other fusion methods. The quantity of data transmitted after the initial image to the merged image is calculated using mutual information.

$$MI = MI_{AF} + MI_{BF} \quad (1)$$

Where,

$$MI_{AF} = \sum P_{FA} log \frac{P_{FA}}{P_F P_A} \quad (2)$$

$$MI_{BF} = \sum P_{FB} log \frac{P_{FB}}{P_F P_B} \quad (3)$$

P is the density of edge_probability, PFA and PFB is the density of joint_probability. It is possible to determine how much information is contained in fusion results by utilizing the entropy:

$$EN = \sum_{i=0}^{L-1} p_i \times log_2 p_i \quad (4)$$

Where, p_i is a Gray level probability distribution with pixel information.The average gradient represents an image's resolution. ΔI has a gradient in all directions.

$$AVG = \frac{1}{MN} \sum_m^M \sum_n^N \sqrt{\frac{(\Delta I_x^2 + I_y^2)}{2}} \quad (5)$$

3.3. Inverse Transform

Once performed a transformation on an image and want to reconstruct the transformed image back to its original form using an inverse transform function with the following pseudocode:

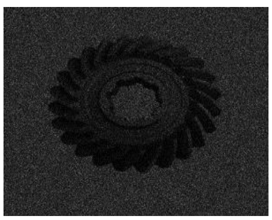
```
def inverse transform(original_image, transformed_image,
transform_function):
   # Apply the inverse transformation function to the
transformed image
    inverse_transformed_image =
transform_function.inverse(transformed_image)
        # Apply the inverse transformation to the original image
    reconstructed_image = inverse_transformed_image +
original_image
   return reconstructed_image
```

In the above pseudocode, the *inverse transform* function takes three parameters: the original image, the transformed image, and the inverse transformation function. Here, we assume that the inverse transformation function is defined and provided separately.

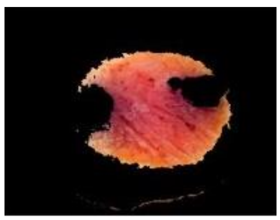
The inverse transformation function transform_function.inverse(transformed_image) applies the inverse operation to the transformed image, recovering the intermediate representation obtained during the transformation process. After that, the visual that has been rebuilt is generated by appending the image that has been inversely converted to the initial image. This step combines the information from the original image with the recovered transformed information to restore the image to its original form.

4. Experimental Analysis

Tsinghua University contributed the X-ray scattering images for this work, while the radar images were created by the National University of Defence Technology's Holographic Subsurface Radar. Figure 4 shows an X-Ray image, radar image and a denoised image. The experimental metal target has a radius of 15 millimetres. The X-ray image is augmented to provide uniformity between the two kinds of images.



X-Ray Image



Radar Image

Dinoised Image

Fig. 4 Aligned images

In theory, weighting fusion is simple to construct but has deprived edge deterrence. With three directional resolutions and the ability to rebuild accurately without losing information, Inverse Transform is well suited for analyzing approximations and detailed information. Nevertheless, it lacks translation consistency. The multi-scale geometric technique solves Inverse Transform shortages and more successfully represents rich textural and high dimensional information, although its density is relatively high, as shown in Figure 5.

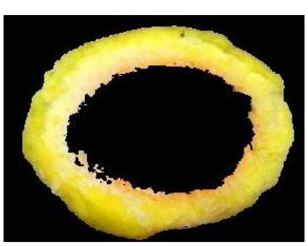


Fig. 5 Fusion result after inverse transform

Radar and X-ray images contain inaccurate information, unlike previous image fusion techniques. The fused image is anticipated to retain more useful information after the image fusion operation. Consequently, subjective analysis must be conducted to determine the fusion method's overall effectiveness.

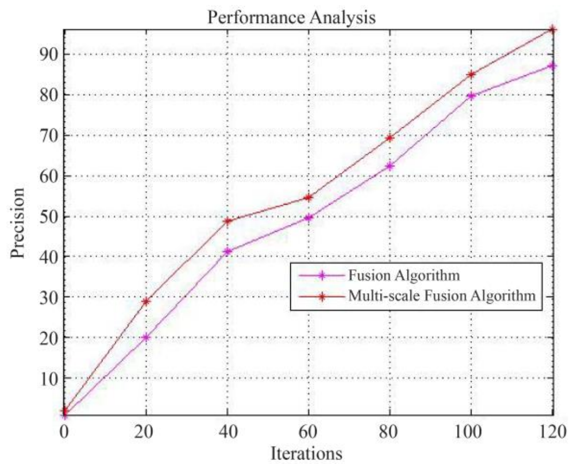


Fig. 6 Performance comparison

This paper compares our proposed fusion algorithm with the normal fusion algorithm. It shows that our proposed model gives better precision than the existing method, as shown in Figure 6.

Integrating multi-scale feature modifications is a fundamental element of the suggested methodology. Various feature representations at varying scales are leveraged in this approach. Hybrid approaches capture fine details and global context simultaneously, which results in better-fused images than traditional single-scale approaches.

5. Conclusion

The qualities of X-ray scatter images and radar images are evaluated in this paper. Denoising an X-ray backscattered image requires simultaneously determining the target's appearance and radiofrequency characteristics.

Multi-scale fusion integrates the recovered targeted image into the Radar image. The basic functions and decompose levels are frequently fixed in multi-scale transform-based algorithms that combine infrared and visible images.

Data-driven selection of the optimal visualization of source images is still challenging, and adapting decomposition levels is also challenging. Flexible basis functions for enabling data-driven selection remain difficult to select. A hybrid method of combining infrared and visible images should combine the advantages of several image fusion techniques to achieve effective results.

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