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Hybrid Invariant Local Feature Extraction for Medical Image Registration

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Abstract: ***In recent decades, Image Registration (IR) is a challenging task due to variation in illumination, resolution of the images, dissimilar perspectives and the local deformations within the image. These difficulties are resolved by an automatic registration scheme based on a hybrid feature combination of Speed up Robust Features (SURF) and Binary Robust Invariant Scalable Keypoints (BRISK). In the registration process, this feature combination speeds up the feature extraction and matching. Here, it makes the matching point pairs distributed consistently in medical images and also further enhance the accuracy of input image rectification. Experimental result proves that the proposed scheme is very significant in IR than the existing methods.***

Key-Words: **Automatic registration, Binary robust invariant scalable keypoints, coarse matching, medical image registration, speed up robust features.**

1.INTRODUCTION

Image registration, also known as image fusion, matching or warping, can be defined as the process of aligning two or more images. The goal of an image registration method is to find the optimal transformation that best aligns the structures of interest in the input images. Image registration is a crucial step for image analysis in which valuable information is conveyed in more than one image; i.e., images acquired at different times, from distinct viewpoints or by different sensors can be complementary. Therefore, accurate integration (or fusion) of the useful information from two or more images is very important. There are two approaches available in Medical Image Registration (MIR) such as Feature Based Method (FBM) and Intensity Based method (IBM). Here, the objective of image fusion is to associate matching information from a medical image of the similar scene by using FBM. Such fused images are more sufficient for further image processing tasks like object identification, regional variation detection and image segmentation. Several FBM techniques have been established over the past few years for correct detection and extraction of objects or important features from medical image. Totally four steps involved in FBM for IR; feature extraction, feature matching and geometric transform and re-sampling.

A frequent problem arises when images taken, at different times, by different sensors or from different viewpoints need to be compared. The images need to be aligned with one another so that differences can be detected. A similar problem occurs when searching for a prototype or template in another image. To find the optimal match for the template in the image, the proper alignment between the image and template must be found. All of these problems and many related variations are solved by methods that perform IR. A transformation must be found so that the points in one image can be related to their corresponding points in the other. So, the descriptor level optimization required in MIR. Features extracted from the medical image might be global or local features. Image pattern of the local features is commonly represented by its edge, corner and points. Here, the selection of feature extraction depends on descriptor and matching scheme. In the IR, BRISK and SURF are widely utilized and shows better performance.

The remainder of this paper is organized as follows. Section II describes background material and related work. In Section III, describes hybrid feature based medical image registration algorithm. Section IV illustrates the registration performance of our method on various types of medical image pairs with comparisons to other approaches, followed by some concluding remarks in Section V.

II .LITERATURE REVIEW;

Stefan, *et al.* [11] developed an elastix, an openly accessible PC program for MIR based on intensity. The software comprises of a set of algorithms that were usually utilized to crack MIR problems. Elastix's modular design enables the user to speedily configure, test, and compare diverse registration techniques for a particular application. Computerized processing of big volume of data sets enables by way of command-line interface through scripting. The use of elastix for comparing dissimilar registration method have been demonstrated with three example experimentations in which individual components of registration method were varied.

Andrea, *et al.* [12] evaluated a new framework for capturing large and complex deformations in IR and atlas construction. This challenging and recurrent problem in computer vision and medical imaging currently relies on iterative and local approaches, which were prone to local minima. Their general framework has introduced a new direct feature matching technique that finds global correspondences between images via simple nearest neighbor searches. More specifically, very large image deformations have been captured in Spectral Forces, which were derived from an enhanced graph spectral representation.

Sascha, *et al.* [13] illustrated a boosting algorithm to enhance existing methods for Deformable Image Registration (DIR). The proposed DIR-Boost algorithm was motivated by the theory of hypothesis boosting, well known in the field of machine learning. DIR-Boost have utilized a technique for automatic registration error detection to obtain estimates of local registration quality. All areas detected as erroneously registered have been subjected to boosting, i.e. undergo iterative registrations by employing boosting masks on both the fixed and moving image.

III. PROPOSED METHODOLOGY

This section broadly describe the proposed approach for MIR. Here, the initial input Medical images are capture from different view-points, at altered times, for identifying and matching of features. Generally, three kinds of feature levels available in image processing such as low level features, descriptor level features, and high level features. In registration, low level features are ineffective in nature as it is not significant towards removing the weak points. Likewise, the high level features are effective, but it shows more computational complexity. Here, the descriptor level features are preferred to perform MIR. The general architecture of the MIR is represented below in figure 1,

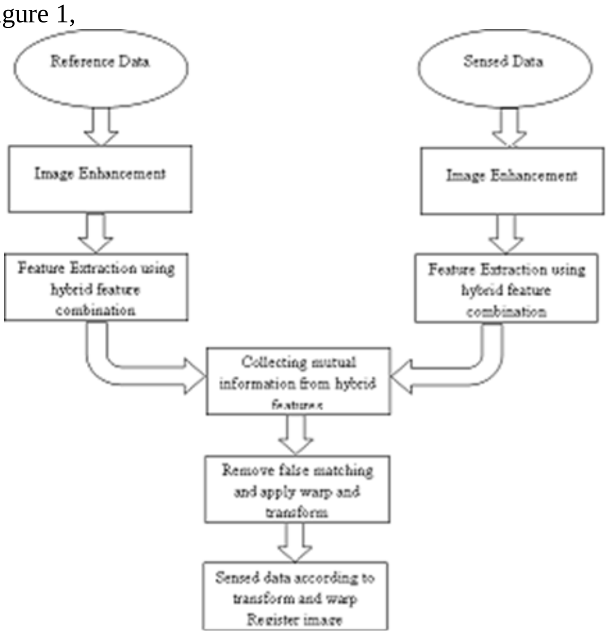

Figure 1. Procedure followed in image registration

IV.HYBRID FEATURE COMBINATION IN MIR

In proposed methodology, by employing hybrid feature selection (combination of SURF and Binary Robust Invariant Scalable Keypoints **(**BRISK)), the global and local level features are extracted from the medical image. The local features are analyzed by utilizing SURF, which is many times faster and more robust in processing several transformations in images than other descriptors and also it is very significant in integral image.Similarly, the global features are separated by employing BRISK, which is implemented with a mechanism of orientation compensation in order to determine the orientation of keypoint and rotation. The following feature descriptors are explained and detailed below,

V.SPEED UP ROBUST FEATURES

The following section summarizes the SURF algorithm, it is a robust local feature descriptor that is widely utilized in computer vision applications. This algorithm contains three major steps such as Interest Point Localization (IPL), Integral Image Generation (IIG) and Interest Point Description (IPD). In SURF, the detection of key points depends on the scale space theory. In order to determine the SURF features in an image I, this algorithm employs fast Hessian detector. Here, the Hessian Matrix (HM) is identified correspondingly to every pixel position of the image I and it is mathematically given by,

$$H(X,\sigma)=\begin{Bmatrix} C_{xx}(X,\sigma) & C_{xy}(X,\sigma) \\ C_{yx}(X,\sigma) & C_{yy}(X,\sigma) \end{Bmatrix} \quad (1)$$

Where, X is represented as the point of image, σ is mentioned as scale,

Normally, $C_{xx}(X,\sigma)$ is denoted as the convolution of Gaussian second order derivative of image at the corresponding point with co-ordinates (x, y). Gaussian second order derivative is represented as,

$$\frac{\partial^2}{\partial x^2} g(\sigma),\ g(\sigma)=\frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}} \quad (2)$$

Likewise, the second order Gaussian derivative for $C_{yy}(X,\sigma)$ and $C_{xy}(X,\sigma)$ are respectively given as follows,

$$\frac{\partial^2}{\partial y^2} g(\sigma) \quad \text{and} \quad \frac{\partial^2}{\partial x\, \partial y} g(\sigma) \quad (3)$$

In SURF, a simple box filter is utilized as the approximation of convolution Gaussian second order derivative in smooth image, it makes the operation with less computational complexity. Here, the box filters are computed in constant time by utilizing integral images and this integral images are employed to achieve convolution of box filters B_{xx}, B_{yy}, and B_{xy}. The approximate determinant of the HM is employed to identify the key-point, which is mentioned as follows,

$$Det[H(X,\sigma)] = B_{xx}B_{yy} - (0.912B_{xy})^2 \qquad (4)$$

Where, 0.912 is utilized to stable the HM determinant,
In order to attain scale invariance, SURF employs box filters on the image to examine and match interest points. Hence, the box filters of altered sizes construct the scale space, which is portioned into octaves. The approximate determinant of HM is determined at various scales and the non-maximum suppression in $3\times3\times3$ neighborhood is implemented to identify the maxima. With the reference of the maximum values, the SURF key point's location and scale σ are obtained. An orientation is allocated to the obtained key-point by determining the Haar-Wavelet (HW) response within its neighborhood radius $6s$ (s means sampling steps).

The next step involved in the SURF feature is extracting the descriptor at the key-point. The orientation direction is allocated to the center of key-point, a square size of $20s$. Respectively, the square size is partitioned into 4×4 sub-regions, each sub-region is further classified into 5×5 sampled space points, at each space point's horizontal and vertical HW response dx and dy are identified. Here, each sub-region generates 4 dimensional vector by employing HW response and it is given by,

$$v = (\sum dx, \sum dy, \sum |dx|, \sum |dy|) \qquad (5)$$

Now, all the sub-regions are concatenated into vectors as $4\times(4\times4)$, which results in 64 dimensional vector at each key-points. The following 64 dimensional vectors are employed in performing the matching procedure.

VI.BINARY ROBUST INVARIANT SCALABLE KEYPOINTS

BRISK is utilized as a texture descriptor, which attains a significant quality of matching with limited computation time and generate a valuable key-points from an image. Here, it employs a symmetric sampling pattern over sample point of smooth pixels in feature descriptor. The intensity of the image is represented as i_x and then employ Gaussian smoothing with standard deviation σ_x, which is equivalent to the distance between the circle and points. The key-point k in an image is patterned according to its scaling and position, the sampling-point pairs are denoted as (i_x, i_y). Respectively, the intensity of smoothed values of points is denoted as $S(i_x,\sigma_x)$ and $S(i_y,\sigma_y)$ helps to determine the local gradients. Mathematically, the local gradients $G(i_x,i_y)$ are represented as follows,

$$G(i_x,i_y) = (i_y - i_x).\frac{S(i_y,\sigma_y) - S(i_x,\sigma_x)}{\| i_y - i_x \|^2} \qquad (6)$$

Assuming, the set A of sampling point pairs,

$$A = \{(i_x,i_y) \in \Re^2 \times \Re^2 \mid x < N \wedge y < x \wedge x, y \in \mathrm{N}\} \quad (7)$$

Where, N is mentioned as the number of sampling point pairs,Partition the pixel pairs into two sub-sets such as short distance pairs and long distance pairs and it is mentioned as d_1 and d_2 respectively. The following equations represent the distance pairing of sub-sets,

$$d_1 = \{(i_x,i_y) \in A \mid \| i_y - i_x \| < \delta_{\max}\} \subseteq A$$

$$d_1 = \{(i_x,i_y) \in A \mid \| i_y - i_x \| < \delta_{\min}\} \subseteq A \quad (8)$$

Analysis, the local gradient in long distance pairs and not necessary in the global gradient information. The threshold distance is set as $\delta\max = 9.75t$ and $\delta\min = 9.75t$ $\delta\min = 9.75t$ (t is the scale of k). Hence, the point pairs are iterated through L to identify the complete pattern direction of key points k, which is given by,

$$G = \begin{pmatrix} G_x \\ G_y \end{pmatrix} = \frac{1}{L}.\sum_{(i_x,i_y)\in L} G(i_x,i_y) \qquad (9)$$

Sampling pattern rotation of orientation is mentioned as $\alpha = \arctan 2(G_y, G_x)$ of the key-point. The binary descriptor b_k is generated by utilizing short distance paring and each bit in b_k is calculated from a pair in F. Hence, the descriptor is $512bits$ long and it is gathered by performing short distance intensity at every binary feature vectors v, it is mentioned as follows,

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$$v = \begin{cases} 1, & S(i_y^\alpha, \sigma_y) > S(i_x^\alpha, \sigma_x) \\ 0, & otherwise \end{cases} \forall (i_x^\alpha, i_y^\alpha) \in F \quad 10)$$

Generally, the MIR depends on affine geometrical transform, the following feature combination (SURF and BRISK) provides a better affine geometrical transform. While matching of two medical image, it contains both inliers and outliers (Inliers represents a correct prediction of features and (Outliers represents a wrong prediction of features). This hybrid feature combination attains a significant rate of inliers.

VII.EXPERIMENTAL RESULT AND DISCUSSION

Experimental outcomes were implemented on PC with 1.8GHz Pentium IV processor by employing MATLAB (version 6.5). In this scenario, the MIR was illustrated in two different ways such as, standard and with noise. Whereas, the sample medical images are mentioned in figure.2.

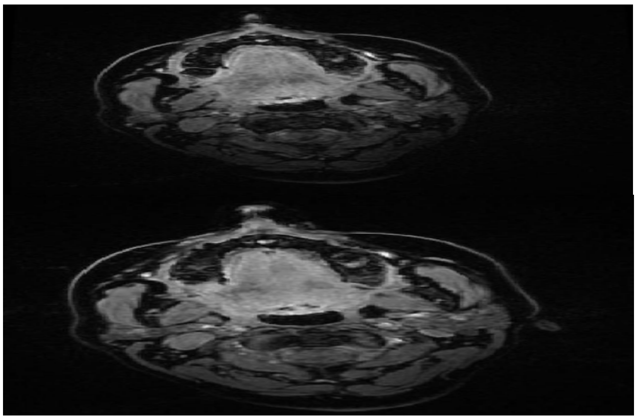

Figure 2. Input medical images

VIII .STANDARD MIR:

Following two medical images were matched by applying BRISK feature. In this feature extraction, the points were detected and matched by computing pair-wise distance method named as hamming distance, which is represented in figure 3. Likewise, in SURF feature the corresponding points were matched by utilizing Sum of Squared Difference (SSD). Matching the point using SURF feature with the combination of (inliers and outliers) and only with inliers are mentioned in figure 4,

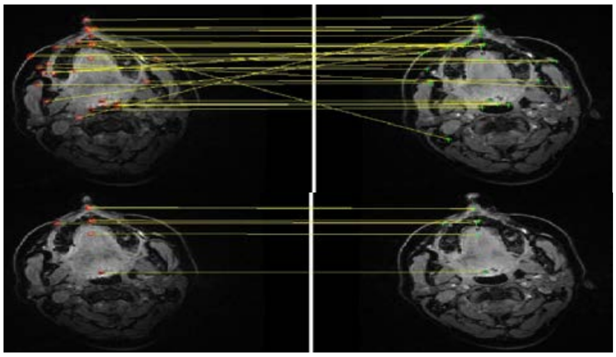

Figure 3. Matching the points using BRISK with inliers and outliers, only with inliers

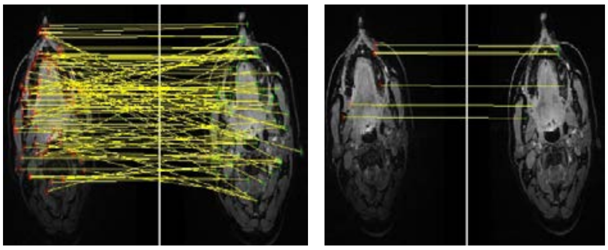

Figure 4. Matching the points using SURF with inliers and outliers, only with inliers

Similarly, in the feature combination of BRISK and SURF, the matched points were combined. Matching the points using (BRISK and SURF feature combination) is specified in figure 5 with the combination of (inliers and outliers) and only with inliers.

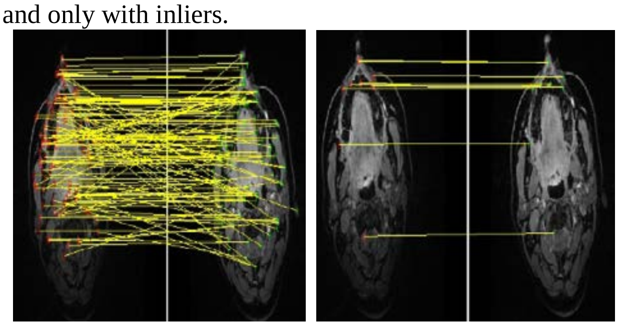

Figure 5. Matching the points using BRISK and SURF with inliers and outliers, only with inliers

In this experiment, the quality of MIR is based on affine geometrical transform. While comparing, the geometrical transforms for BRISK and SURF provides a comparable results. But, the combination of BRISK and SURF delivers an effective matching result in registration. The final output of BRISK, SURF and the combination of BRISK and SURF are specified in the figures 6, 7, and 8 respectively,

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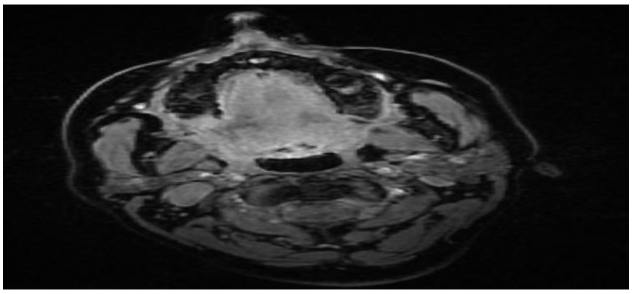

Figure 6. Image registration using BRISK

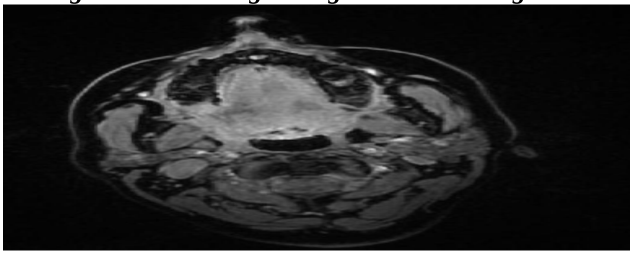

Figure 7. Image registration using SURF

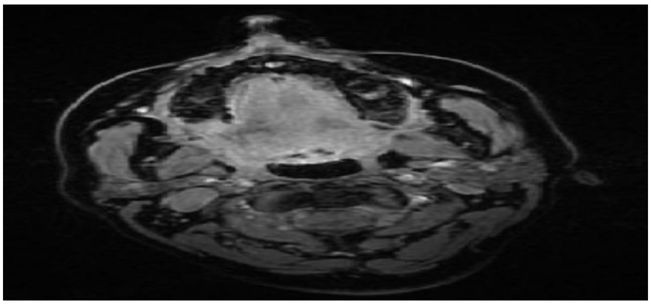

Figure 8. Image registration using combined BRISK and SURF

IX.MIR WITH NOISE

Generally, two medical images are essential to perform MIR. In that, the first image is stationary and the second image is going to register in the first image. Here, MIR with noise demonstrates, including the noise in the second image. Whereas, the noise factor did not affect the efficiency of repeatability and inliers ratio rate. The final output of SURF and BRISK combination with noise is mentioned in figure 9,

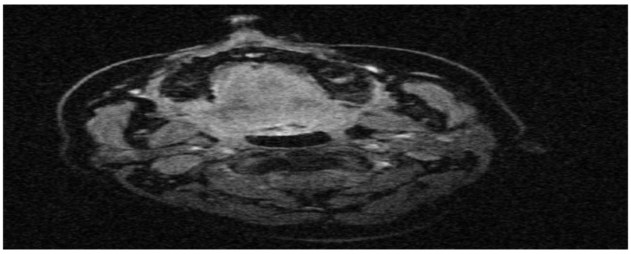

Figure 9. Image registration using combined BRISK and SURF with noise

X.ANALYSIS REPORT

The accuracy of IR is based on two factors inliers ratio and repeatability. Inliers ratio determines the correct prediction rate of feature matching and the repeatability is determined by the mean of detected key-points. Here, the MIR is demonstrated in two different ways like standard MIR and MIR with noise. Experimental outcome clearly shows that the combination of SURF and BRISK provides a better registration than two existing methods. The performance analysis of features are graphed below in figure 10 and 11 respectively,

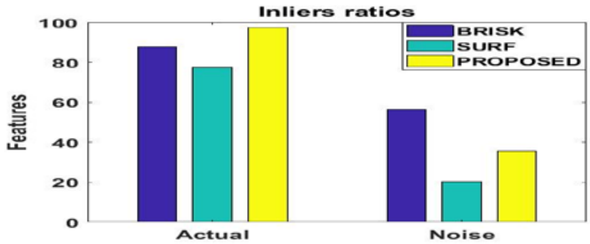

Figure 10. Inliers ratio comparison

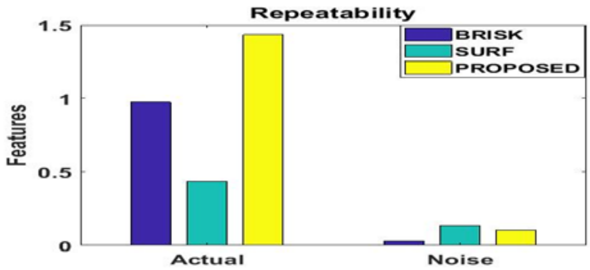

Figure 11. Repeatability comparison

The performance evaluation of feature combination and the individual methods are evaluated in Table 1. Hence, it proves that the proposed feature combination is very effective in IR than the other two individual methods.

	Standard			With Noise		
Methods	BRISK	SURF	SURF+ BRISK	BRISK	SURF	SURF+ BRISK
Inliers Ratio (%)	87.71	77.46	97.56	56.29	20.24	35.71
Repeatability	0.976	0.437	1.433	0.030	0.134	0.063

Table1.Performance Evaluation of feature combination

Conclusion

This paper evaluates a hybrid feature combination (SURF + BRISK) for improving the MIR. Usually, the performance of the IR depends on inliers ratio and repeatability. In this scenario, the MIR is illustrated in two different ways such as, standard and with noise. At standard MIR, the inliers ratio and the repeatability of proposed combination showed 97.56% and 1.433 values respectively. On the other hand, MIR with noise showed a superior result in terms of inliers ratio and repeatability, which is significantly greater than the other two individual methods. After performing the descriptor level feature combination, the outcome of registration is very impressive.

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