Image Stitching of the Computed Radiology images Using a Pixel-Based Approach

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Abstract

In this paper, a method for automatic stitching of radiology images based on pixel features has been presented. In this method, according to the smooth texture of radiological images and in order to increase the number of the extracted features after quality enhancement of initial radiology images, 45 degree isotropic mask is applied to each radiology image to observe the image details. After this process, we used statistical and heuristic image noise extraction method (SHINE) to acceptably reduce the noise resulting from radiation of alternating X-rays on detector. Pixel point's features are obtained by selecting maximum or minimum value of the brightness of pixels in certain neighborhood of the resulting radiology images. This algorithm transmutes point's features to 128 dimensional vector features. In order to identify the segments overlapping in basic radiology images, we specify equivalent vector features of each radiology image using the mathematical properties of the vectors and find the fit geometry transform between pairs features matched by the random sample consensus (RANSAC) algorithm. Finally, resulted motion model is applied to the initial radiology images and we stitch them together in a common surface.

.Keywords: radiology images automatic stitching, 45 ° isotropic mask, statistical and heuristic image noise extraction (SHINE), random sample consensus (RANSAC).

1. Introduction

Typically field of view in pin-hole cameras and detectors is limited so that images captured using of this cameras and detectors can't effectively be used to fully understand the information environment. Solving this problem, using images captured by multiple cameras or detectors separately with different shooting angles improves the resolution and obtaining complete information from the object, although this method cannot be advantageous for the user to analyze the resulted images separately [1]. In this case the image stitching algorithm is used to improve the overall performance.

Image stitching algorithms represent methods to stitch integrated and seamless multiple images with overlapping regions, to achieve the image with higher-resolution and wider-viewing angles. Using these methods, a user can observe the full image in the resulting stitched images at once [1, 2, 3, 4, 5, 6].

Image stitching algorithms are composed of two parts: image registration [7] and image blending [2, 8]. Image registration methods are the operations for alignment of two or more images of a subject [9] and are the basis of images blending. So that the image stitching techniques considering their mechanism of performance registration methods are divided into two types named direct and based on features [2, 10].

In the direct method, the similarities between the basic images pixels are calculated by minimizing a correlation error function and the overlapping regions are specified. Then matching the initial images overlapping regions onto each other and

using the brightness adjusting methods are performed and the stitched image will be achieved [2]. In feature-based registration method which is based on
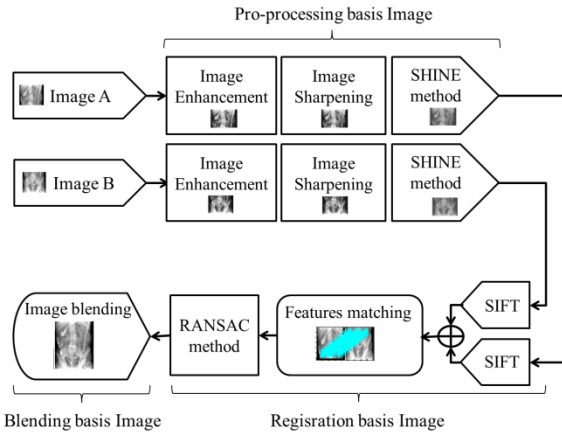

Fig.l. Block diagram of the proposed method for automatic stitching radiology images based on pixel-based features.

image data, the characteristics of the basic image are extracted to find shared information between them [1, 2]. Such methods reduce the domain search for the common area between the two images.

In radiology images in order to display the human body or long parts, e.g. legs or spine, that are longer than a common screen-film sheet or blue film cassettes, the images half parts of the organs are stitched together [3, 11]. In this case, when the detector is moving to the next position between subsequent exposures, it is likely that the patient moves because of the pain or intense breathing and this will create paradoxical contacts in fundamental images [3, 4].

To resolve this problem in the field of radiology images stitching, an algorithm is required to be sustained against rotation, scale changes, blurring and ghosting caused by motion [2, 5]. Automatic stitching, proper speed [6, 12], resistance to changes such as ghosting and blurring caused by motion [5, 6] and also proper implementation price of feature-based stitching algorithm, causes the priority of usage, so that today, all new stitching algorithms are presented based on this principles [2].

The main step in the implementation of such algorithms is feature extraction from basic images. These features must be selected in a reasonable manner. The extracted features, according to the basic images conditions and the type of application, must have the following properties.

- *Invariance***:** The selected features should be invariable against scale changes, illumination and angle rotation.
- *Locality***:** Extracted Features should be robust with occlusion and clutter.

- *Distinctiveness:* A feature ability to represent the important pixels or sections of the image easily for large database of objects.
- *Quantity***:** Many features could be extracted even from small objects.
- *Efficiency***:** Computing the time and process for feature extraction should be reasonable.
- *Repeatability***:** if a feature located in the overlapping region of the initial stitch candidate images, then it should be extractable from all images [13].

Features extracted from images are based on boundaries, areas and pixels [14]. In radiology images stitching using the methods based on features due to blurring and ghosting caused by the patients move [2, 3, 4, 5, 6], generated noises due to the continuity X-ray radiation dose on the detector and occlusions which will occurred by the probable preservatives of patients [3, 4], use of features based on the areas and boundaries do not have desired effect in some cases.

According to above review, the best feature types for radiology images stitching are features based on pixels. However, these features are very sensitive to texture images, but by increasing the number of the extracted features using some preprocessing techniques, better conditions for quick and qualified stitching is provided.
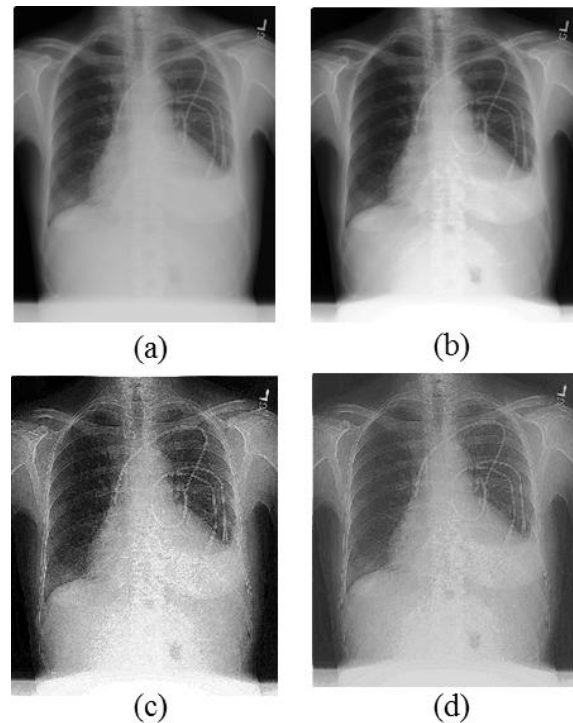

Fig.2. This image shows pre-processing steps occurred on the initial images. In (a) the original input image is shown without any

changes, (b) shows the X-ray image after image enhancement. In (c) in order to display better, image brightness radians is added to the image and (d) shows the result after applying Shine algorithm by the reconstruction factor of 48 to 64.

For this purpose and before the point's features extraction, a pre-processing should applied to the images. This pre-processing consists of three steps including quality improvement, image sharpening [14] and noise removal from the initial images [14]. Then the features are extracted from the processed images. Finally, to achieve a stitched image similar to the original segments images [15, 16], the important and consistent coordinates will be transferred from the pre-processed images to the original images and by using a motion models they will be stitched together.

2. Proposed Method

2.1. Radiology image pre-processing

Normally the images are displayed with two-dimensional matrix of real, integer or binary numbers. Each element of this matrix is called a pixel. To storing digital radiology images the digital imaging and communications in medicine (DICOM) format was used. Dicom standard is a joint project of the American College of Radiology (ACR) and National Electrical Manufacturers Association (NEMA).

This standard are provided to generalization and communicate medical imaging equipment with one set of media storage services that helps to assimilate file format and simplify access to images and data stored on them. In radiology images, soft tissues of the body such as muscles are displayed murky and bones and cartilaginous tissues are displayed white.

In these images, the boundary between these two texture or details and edges of the bones and muscles are not fully understood due to the difference types of the cassettes and radiation dose and the obtained image quality is not acceptable.

Edge is the part of an image that the brightness is broken in that area. Since usually the points with the maximum value of the brightness is created from confluence of two ascendant edges and the points with minimum value of the brightness is created from confluence of two descending edges, it is necessary that at first the quality, clarity and brightness changes in the image edges are improved. Then the maximums and minimums of the brightness are extracted more easily and preciously.

For this purpose and in first step, the original images quality is improved [17]. The brightness histogram of initial images should be expanded so that the obtained histogram is balanced and include all the brightness levels dependent on the image bit depth.

After the initial image quality improvement and in order to enhance the edges clarity, the image

$$c_k(\text{i}) = s_{tol}^{\frac{1}{2}} \sum_{j=1}^{n} \frac{x_{ij}}{s_i s_j^{\frac{1}{2}}} u_k(j)$$

$$d_k(j) = \frac{1}{\Upsilon_k^{\frac{1}{2}}} \sum_{i=1}^{p} \frac{x_{ij}}{s_j} c_k(i)$$

$$xr_{ij}(q) = \frac{s_i s_j}{s_{tol}} \sum_{k=1}^{q} \frac{c_k(i)d_k(j)}{\Upsilon_k^{\frac{1}{2}}}$$
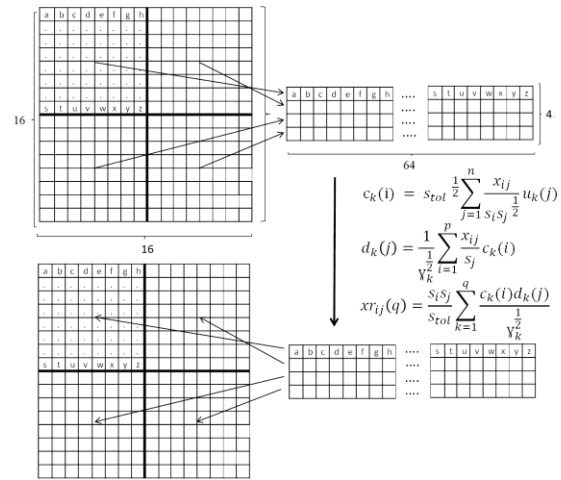
Fig.3. Shine filter operation process steps.

details must be expressed more preciously. Since the details of an image is provided by the high frequency information the gradient of the image could be calculated and added to the image to enhance the overall resolution. This process is achieved by applying a sub mask such as eq. 1 on the image [17].

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix} \tag{1}$$

After image sharpening by using the SHINE method, the adverse effects created by applied mask on the images and also the noises in the radiology images is reduced.

In SHINE method, images is divided into blocks of $m \times m$ pixels (see Fig.3.) and then pixels of each blocks is arranged in a row of a matrix. According to the image size the converted matrix $X(p, n)$ has p rows and n columns. Each row of this matrix represents a block and each column of this matrix is accordance with a pixel of the blocks [18].

This method is extracting a subset of q dimension from the X matrix which $q<<n$. Extracted q coefficient of the X matrix represents important information existing in the original data set and the remaining coefficients ($n-q$) contains less important or unwanted information such as noises [18].

The q coefficient is obtained by using a statistical combination of the eigenvalues and eigenvectors of each block of the image so that the output image quality is dependent on the number of statistical factors used for image reconstruction [18].

2.2. Feature extraction from radiology images

To stitch radiology images using pixel-based features, for some reasons such as rotation and distortion arising occurred during image cassettes

transportation to the digital systems, the detector or patients may move between two successive exposure and by considering the smooth texture of these images, it is need to extract those types of the features, that are stable in the face of the changes against rotation, blurring and ghosting caused by patient motion and occlusions.

In [10] a method was presented based on maximize or minimize of the brightness value for each pixel in a certain neighborhood and in a certain scale of an image with a 128 dimensional vector. Feature vectors obtained from this method are invariant against rotation, scale and illumination. The proposed method is called **Scale invariant feature transform (SIFT)**. Feature vectors detection using this method is performed in four stages.

1) Maximum or minimum scale space detection: In this stage a search is done to find pixels by the maximum or minimum brightness value on all possible scales [10]. An inherent property of objects in the real world is that they exist only as existence meaningful in the range of a certain scale. So in order to get the specific features on the certain scales, it is needed that all possible scales of an image included. This space is called the scale space.

Scale space is a cascaded filtering method which can find a specific object in the captured images with different scales. In order to detect a situation which is appears by different scales on individual images is done using scale invariant features [19].

In the SIFT method, scale space is obtained from subtracting the results of the applying Gaussian filters on images that have a certain scale difference (see Fig.4.). Consider the studied image as $I(x, y)$ then the scale space is constructed as eq. 2.

$$DOG = \big(G(x,y,k\sigma) - G(x,y,\sigma)\big) * I(x,y,\sigma) \quad (2)$$

In (2), k is a constant number and the Gaussian filter is obtained using $\frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$. In this equation, the width and height of Gaussian window is shown with x, y and the scale with σ as well. Since the Gaussian kernel removes high frequency components and it retains spatial information between two frequency ranges then the obtained result will be a Band-stop filter [20].

After obtaining the scale space, in order to detect the points with the maximum or minimum brightness values, each pixel is compared with eight neighboring pixels on the current scale, nine neighboring pixels on the scale above and nine neighboring pixels on the scale below. It is done if and only if the brightness value of the point was larger or smaller than these 26 pixels. It is selected as a candidate afterward.

The processing time is low reasonably because more sampled points are removed by initial examining. One of drawbacks of this method is the inability to determine the minimum distance between
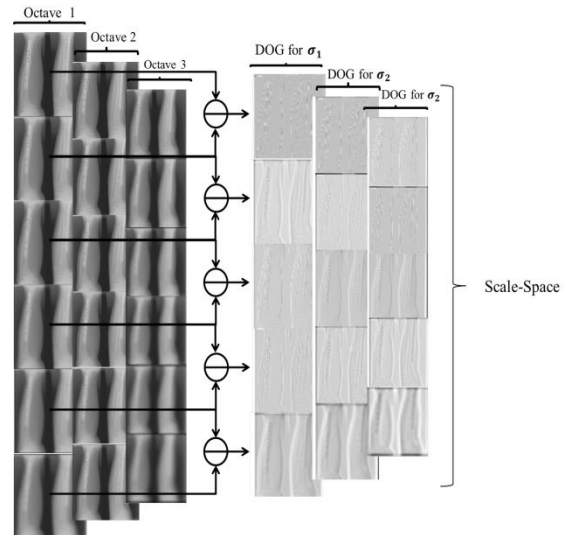

Fig.4. In this figure, an example of the scale (DOG) used in the SIFT method for a radiology image is shown. This space is obtained in the three-level scale due to the use of the smooth texture image.

the detected all extrema, so the extrema can be chosen freely close together. In fact the extrema that are located close together, even are unstable against small perturbations on the image [10].

2) The exact location of the point's features: As it is discussed, one candidate of the point's feature is obtained by comparing it with its neighbors. The next step is deleting the features that are sensitive to the noise and distortion. For this purpose, the candidate points that have low contrast, small distance relative to each other and or are located along the edges (see Fig.5.(a)) should be removed [10].

3) Assign orientation to the feature points: By assigning a fixed orientation based on local properties of the image on the key points, the feature descriptor can show a correlation with this orientation until feature vectors get invariance regard less of the image rotation. For this purpose the histogram composed of the gradient magnitude and orientation achieved of pixels that are in a certain area around each key point, is used.

This histogram has 36 bins that each bin is composed of 10 degrees. In the orientation histogram calculated for orientation assignment to each point feature detected as the highest peak and any other peaks that is 80% of the highest ever detected peak [6]. Thus, for every feature point there exists at least one certain orientation (see Fig.5.(b)).

4) Acquiring feature vector: To obtain the feature vector first, in scale of point's feature, the smoothed

Gaussian image is selected and the magnitude and orientation of the gradient of the pixels in a 16×16

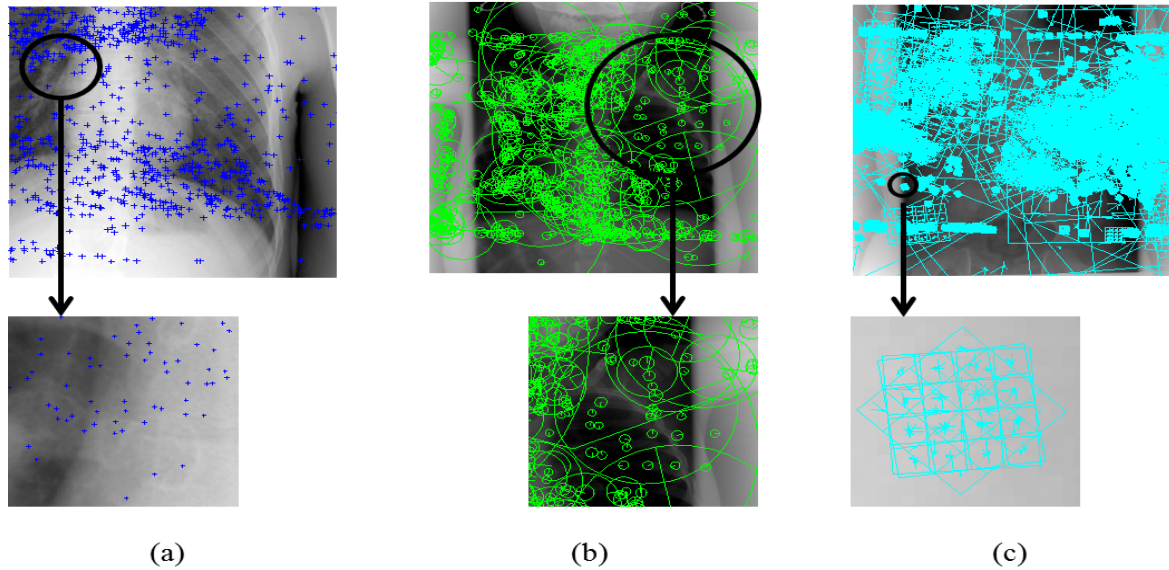window to central feature point is computed. To obtain invariance feature descriptor

(a)   (b)   (c)

Fig.5. In this figure, the location, orientation and the features vectors are shown. (a) shows the location of features with two characteristic x and y. (b) shows the features orientation in the specified location. Scale features are determined with the size of the circles. Features with larger circles have more scale and vice versa. The position of the radius in these circles indicates features orientation. Considering the size of the gradient in a neighborhood of feature's location it is possible to allocate more than one orientation to each position. In (c) feature vectors are formed with respect to position and orientation of features by using local gradients of a 16×16 neighborhood around each location. These vectors for each location, scale and orientation are 1×128 dimension in size.

against rotation, images coordinates and gradient orientations must be aligned with direction feature points (see Fig.5.(c)).

To avoid sudden changes of features due to the small displacement in the position of the windows and also reducing error effects of the gradients registration that are farther from the windows center, a Gaussian weighting function with a scale equal to the width half of selected window around the point's features is used.

The experiments described in [10] indicate that in calculation of the feature vectors , allocating eight orientations for each bin of orientations histogram which were obtained from a 4×4 selected window led them to the best results. Thus, each feature vector will have $128 = 8 \times 4 \times 4$ dimensions.

2.3. Matching the feature vectors of base images:

The most important part in the process of stitching images is overlapping regions detection between basic images, so if the area specified correctly, image stitching flawless is guaranteed. Because, the stitched area is common between images, features extracted from this area also should be common between vectors.

To determine the common area between two initial images based on features method, after extracting basic image features, they must be properly matched with each other to determine

similar features and common areas. Whatever the number of correctly matched features is greater, the size of the overlapping area is determined more accurately.

As it was observed in the SIFT algorithm, after determining the location, orientation and the scale of point's features, a 128 dimensions feature vector is assigned to each of them, and for the matching features vectors it is obtained from basic images and can use as vectors properties.

In this paper, for matching feature vectors the inner product method are used. Inner product of two vectors is equal to multiplication the sizes of two vectors in cosine of the angle between them. So if two vectors were similar, the angle between them is close to zero and the cosine of this angle is maximal. So for the two vectors named $\hat{I}_L(U,V)$ and $\hat{I}_R(U,V)$ the similarity is calculated as eq. 3 and 4.

$$C_{NC}(d) = \sum_{(U,V)\in W_m(x,y)} \hat{I}_L(U,V) \times \hat{I}_R(U-d,V) = W_L . W_R(d) = cos\theta \tag{3}$$

$$d^* = argmax\ _d W_L . W_R(d) \tag{4}$$

In these equations, d represents the angle value between two vectors.

2.4. RANSAC algorithm:

Many of the feature vectors obtained from a basic image do not have properly matched with obtained feature vectors from other basic image. This error occurred due to the features which are extracted from background or it occurred because they are not detected in another image. For stitching primary images together, a homogeneous matrix should be calculated between them. Homogeneous matrix defines a motion model between the overlapping regions of two basic images as eq.5.

$$P_b' = H_{ab}P_a \tag{5}$$

Here P_a and P_b are points matched for basic images A and B [21]. So if the feature vectors were not matched accurately, the motion model could not be identified correctly between them. To eliminate the wrong matching and obtaining a model that was correct for the maximum number of matched features, we use the RANSAC algorithm. RANSAC is an iterative method which estimates parameters of a mathematical model from a set of observed data.

In implementing this algorithm, it is assumed that the data is contained the inliers and outliers. Inliers are a set of the information that is useful to express the model parameters and outliers are other set of the information that is not suitable for the model [21].

In the presented method, outliers are maximum or minimum values caused by noise, incorrect measurements or incorrect assumptions about the state of information. Ransac algorithm runs with a premise achieve to a set of inliers.

The input of this algorithm is a set of the observed data and a suitable parametric model assumed for the observations. RANSAC acquires its goal by selecting a random subset of the original data. This information are assumed inliers and these assumptions are tested as follows:

1) A suitable model for the hypothetical inliers is obtained by calculating all the free parameters of the model for inliers.

2) All other information which is useful for testing the model will be considered as a hypothetical inlier.

3) If the estimated model has a large number of points classified as inlier hypothetical, it is a good model.

4) Because the model was estimated only for the initial set of inliers, again it will be evaluated for all inliers hypothetical.

5) Finally, in order to assess the accuracy of performance, error models are estimated than the inliers attributed to the model.

The above steps are repeated with a predetermined number sequentially. In each iteration, a model is removed due to a few points classified as inliers and a model with a similar measurement error is improved, so the new model is held if it had less error than stored previous models [21].

2.5. Images blending:

Images blending have different methods. In this paper, we have presented a simpler way of images blending. Methods used for this purpose is based on the mathematical relations and conversion of a basic images coordinate system.

The result obtained by this method is highly dependent on the transformation matrix results of registration algorithm, so if the suitable number of features is obtained of overlapping area between two images, success of image blending algorithm is imminent.

In this method, after image registration, using motion model obtained of the matched features, we find the common area between the initial images with convert one of the initial images by motion model. We transfer the old coordinates of another image to the new coordinates of the image that map matrix was applied on it and after common region removal from basic image, two images is stitched together.

3. Results

The input primary images of the stitching algorithm have been selected from different parts of the body. In these images shots of the chests and spines have more texture than legs and abdomen. It should be noted that stitched image resolution completely depends on size of the overlap area between basic images and their content.

The stitching process using described method is consists of three stages: pre-processing, image registration and image blending. In the first stage a pre-processing is applied which consists of three stages named enhancement, image sharpening and removing noise and undesirable effects resulting from the applied sharpening mask in order to increase the number of the extracted features of basic images (see Fig. 6.(b)).

The number of extracted image features increases by basic images enhancement and edges sharpening of basic images in cases compared to the their original state to 700 times but because some of the radiology images have very small texture, this number of extracted features is insufficient for stitching two images and need to apply the algorithm to increase the number of features.

In image registration stage, using SIFT algorithm, selected point features are converted to 128 dimensions vectors. Using the inner product extracted vectors could be matched from each image and then by using RANSAC algorithm transformation matrix between each pair of matched feature vector is obtained from basic images (see Fig. 6.(b)).

By using SHINE algorithm in most radiology images, for reconstruction coefficients (q) of 48 to 64 features extracted increased to amount 15 percent.
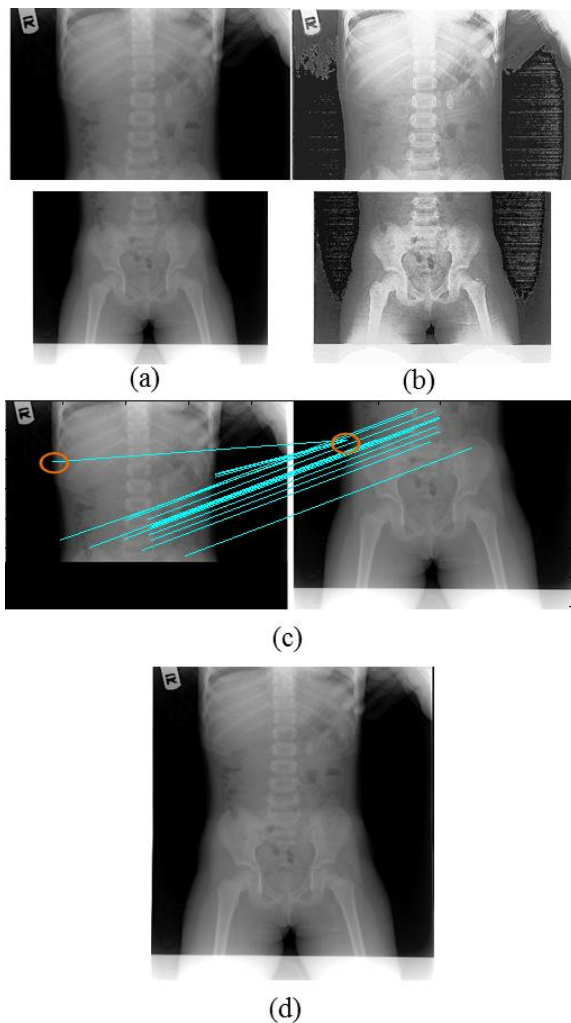

(a)   (b)

(c)

(d)

Fig.6. In this image, the results obtained from various stages of the proposed stitching method are shown. (a) shows two image input to the algorithm. In (b) input images are shown after applying the various stages of pre-processing. As can be seen, the details are more visible in these images. In (c) matched features are connected together with blue lines. In this image occurred a matching wrong because features extraction of the background data. Matches error marked with the red circles. (d) as shows a result of the seamless stitching between two images using of blending method described in this paper.

In the final step, coordinates of the images using obtained mapping matrix is transferred to the same surface and basic images are stitched together on that the surface (see Fig.6.(d)).

Images obtained in this method will have acceptable stitching if the gap of overlapping region is non-visible in them.

4. Conclusion

In this paper, a method for automatic stitching of radiology images based on pixel-based features was presented. In most of the methods used for medical images, especially X-ray images, due to the smooth texture of these images the direct method is used and in few existing feature-based methods for images, denotative occurs in tested images and different body parts was not processed. Further reasons for selecting method based on features for connecting radiological images are not expressed clearly.

Described above method with high accuracy will stitch radiology images with common regions, automatically in two-dimensional surfaces and form seamless image and may have found practical applications in medical stitching softwares.

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