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Full Length Research Paper

3D stereo reconstruction using sum square of difference matching algorithm

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In this study, the Sum Square of Difference (SSD) matching algorithm is introduced to solve the matching ambiguousness between pixels using Quickbird images. This method is tested with three different types of template sizes of 3 × 3, 5 × 5 and 7 × 7 to acquire the best correlation of patches to be correlated. The matching is implemented with two different locations in the Quickbird images. The result shows that template size of 7 × 7 is most appropriate for matching with integrating of sum square of difference (SSD) matching algorithm. The correlation for first matching using template 7 × 7 is 0.8170 and for second matching is 0.8320. The RMSE for first matching is 8.51 and second matching is 8.332. First matching procedure shows lower value of matching pixels percentage value of 72% compared to second matching procedure with a percentage value of 76% pixels. It can be concluded that sum square of difference (SSD) is an appropriate method to solve the matching ambiguousness in high-resolution image such as Quickbird satellite data. It can be said that SSD matching algorithm can be used to acquire more accurate results for matching procedure.

Key words: Quickbird satellite data, sum square of difference, 3D stero reconstruction.

INTRODUCTION

Image processing requires standard mathematical procedures to understand the complexity of features detection and matching (Zaki, 2007; Messaoudi et al., 2007; Stephen, 2009; Adeyemo and Fred, 2009; Mehmet, 2009; Ugwu, 2009; Akintorinwa and Adesoji, 2009; Boumaza et al., 2009; Anjamrooz, 2011; Anjamrooz et al., 2011; Khadijeh et al., 2011; Guillermo et al., 2011; Murat, 2011; Mustafa, 2011; Mustafa and Nihat 2011; Hassasi and Saneifard (2011); Majid and Gondal (2011)). Image matching is a tremendous difficulty of computer visualization and widely exploit in 3-D model reconstruction, object recognition, image alignment and camera self-calibration. Recently, image-matching technique exploited to remote sensing data to search for corresponding points or features between images within the different period of acquisition.

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Incidentally, image matching technique has potential for several applications such as camera stabilization, object detection, tracking of moving objects and image compression. Generally, image matching techniques are implemented to stereo images for certain satellites. Several studies have exploited image matching techniques with high resolution satellite data of IKONOS and QuickBird to investigate and analyz the discrepancies, mismatch and matched of pixels to achieve sub pixel accuracy (Adjouadi and Candocia, 1994; Fuse et al., 1999). In computer vision and image processing, there are three stages involved in feature point matching: (i) feature point extraction; (ii) feature point matching; and (iii) outlier elimination. Algorithms for feature point extraction involve nonlinear filter, curvature and the change of pixel intensity. Stephen (1992) proposed to a nonlinear algorithm which relates each pixel to an area centered by the pixel. In this area, all pixels have similar intensities as the center pixel. This can suppress noise effectively; for it does not need the derivative of image (Stephen, 1992).

According to Kitchen and Rosenfeld (1982), the curvature algorithm needs to extract edges in advance and find out the feature points using the information about curvature of edges. Kitchen and Rosenfeld (1982) stated that the curvature algorithm requires complicated computation; for instance, curve fitting, thus their speeds are low. According to Zhou and Shi (2001), the change of pixel intensity is based on Harris and Stephens (1988) method. It produces corner response through eigenvalues analysis. In addition, this algorithm has fast speed, since it does not require to use the slide window explicitly. This method, nevertheless, is sensitive to noise for the use of first order derivative of image. Researchers have agreed that the result of feature point matching is extremely affected object occlusions, lighting conditions and noises. Consequently, it is crucial to use an appropriate robust algorithm for feature point matching. Zhou and Shi (2001) extended the method for standard assignment algorithm to solve extended assignment problem and proposed a new feature point matching algorithm. They implemented the condition that the depth of the scene is local continuous as extra constraint and used the method for extended assignment problem to do global optimization. Additionally, they stated that robust algorithm requires two optimizations and can be imposed with almost complete matrix computation, as a result, its efficiency is higher than conventional algorithm. Nevertheless, feature based matching needs one to calculate the features of edges or areas. On the contrary, the cost of computation is extremely high. Under this circumstance, these features are more abstract descriptions of the content of the image. Further, under different lighting conditions and the wide baseline transform, these features are invariant (Daniel and Kleinberg, 1994; Zhou and Shi, 2001).

Particularly, Gruen (1985) has stated that window based image matching involves matching of pixels from stereo images. Thus, the pixels matching can exploit by using appropriate templates to find its location, moreover conjugate points (Gruen, 1985). Besides, Karabork et al. (2002) stated that accurate image matching methods rely on the proper size of the selected template. Consistent with Blake et al. (1994) and Karabork et al. (2002), the template matching methods determine the similarity between template windows in two images. Acquiring an excellent matching between pixels, identification or convolution must be carried out to avoid noise impact on areas based matching. The sum of square difference (SSD) matching algorithm is an area based matching technique which involves different size of template in searching for its matching pixels in the right image of the stereo pair. By imposing different sizes of templates, the search and correlation of matching pixels are different. Besides, the search of matching pixels from different sizes of template produces different results. Generally, in sum of squared differences (SSD), the differences are squared and aggregated within a square window and later optimized by winner-take-all (WTA) strategy. This measure has a higher computational complexity compared to SAD algorithm as it involves numerous multiplication operations (Scharstein and Szeliski, 2002). In this paper, the sum of square difference (SSD) matching algorithm is exploited to implement matching of pixels between stereo images. The matching algorithm used is an area based matching technique. The concept of SSD matching algorithm is based on a 'template' from the left image and 'search window' from the right stereo images. Template with selected kernel size is used to search for its conjugate value in the search window (Shahrudin, 2001). It is necessarily to work out the size of kernel whether it is small or large. If the size of kernel window is too small, it may not cover enough intensity variation and must be larger to include enough intensity variation for reliable matching. In contrast, Kanade et al. (1994) stated that assumption for the size of kernel used in area based matching must be small to avoid effects of distortion but must not be too small.

The main contribution of this work is to exploit SSD matching algorithm to reconstruct 3D stereo from high resolution Quickbird satellite images. We hypotheses that: (i) image matching technique can determine the match of pixels of similar features, (ii) using different size of templates can determine the correlations of pixels, and (iii) template window size can impact the accuracy of the SDD matching algorithm.

ALGORITHM

Sum square of difference can be described as a combination of area based and edge-based matching. In photogrammetry, match technique is applied to generate digital terrain model (DEM), detection and measurement of fiducially marks, stereo model points and measuring and transferring tie points between two or more images. To acquire and produce better match, the consideration of image shaping parameters (geometric correction) and radiometric correction were needed. Corrections are needed to remove noise errors which are included in both left and right images. Applying to the 'square of difference' matching technique with stereo images could produce high accuracy of matching (Gruen et al., 1985). Figure 1 shows the block diagram of SDD matching technique that is applied to pair of stereo Quickbird satellite images with pixel size of 0.6968 m.

Stereo epopolar

Stereo epipolar is generated to create a parallel line to ensure that point in left image is corresponding to the same point in the right image. Epipolar is implemented to stereo images to eliminate the Y parallax due to differential of height while the satellite captures the image

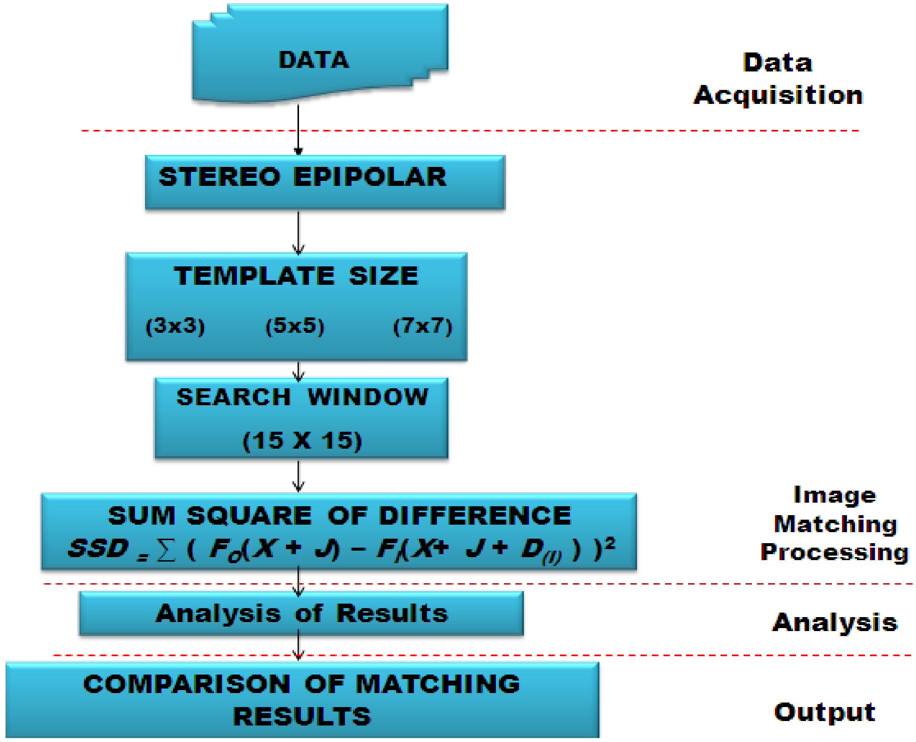

Figure 1. Block diagram of SDD matching procedures.

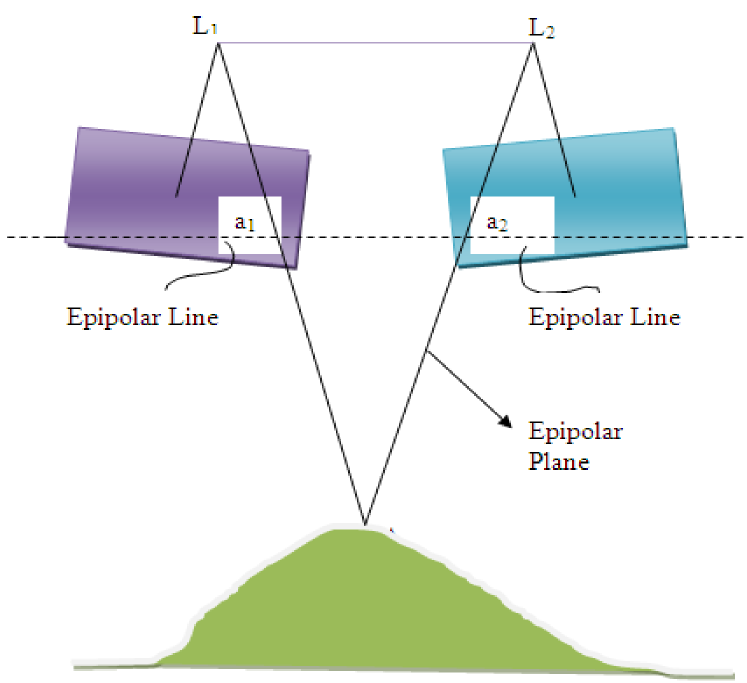

Figure 2. Epipolar plane and lines (Edward et al., 2001).

of the scene. If one point on epipolar line in the left image is projected to the ground, the corresponding point in the right image should intersect on the same location on epipolar plane (Figure 2) (Edward et al., 2001). Unlike

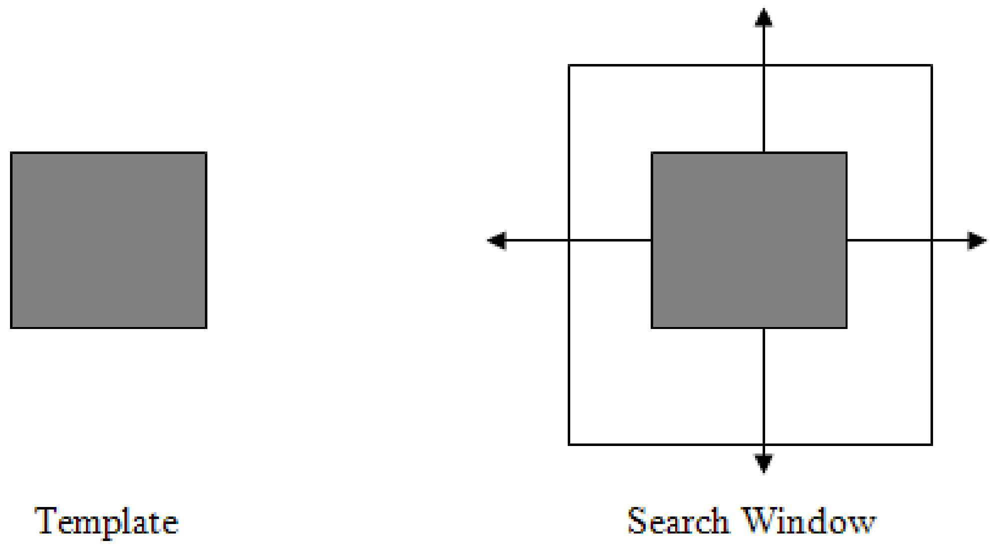

Figure 3. Moving template in search window.

frame-based imagery where all pixels in the image are exposed simultaneously, each scan line of the QuickBird image is collected in a push broom fashion at different instant of time. Thus, epipolar lines with linear CCDs become curves. Using Orun and Natarajan' sensor model (Adjouadi and Candocia, 1994) which models the position of the sensor and its yaw angle variation as second order polynomials of scan line (or time), and assuming the pitch and roll angles to be constant, the derived epipolar curve for a certain point shows a hyperbola-like shape. It can be approximated by a straight line for a small length but not for the entire image. An epipolar curve for the entire image can be approximated only by piece wise linear segments. An epipolar line is created using the collinearity equation which is adopted from (Adjouadi and Candocia, 1994):

$$x = -f\left(\frac{m_{11}(X-X_L) + m_{12}(Y-Y_L) + m_{13}(Z-Z_L)}{m_{31}(X-X_L) + m_{32}(Y-Y_L) + m_{33}(Z-Z_L)}\right) \quad (1)$$

$$y = -f\left(\frac{m_{21}(X-X_L) + m_{22}(Y-Y_L) + m_{23}(Z-Z_L)}{m_{31}(X-X_L) + m_{32}(Y-Y_L) + m_{33}(Z-Z_L)}\right) \quad (2)$$

Where f is template grey-level matrix (m), and (X_l, Y_l) are epipolar curve for point (X_l, Y_l) in the left QuickBird image is approximated by a quadratic polynomial and has the following form:

$$Yr = (A_1X_L + A_2Y_L + A_3) + (A_4X_L + A_5Y_L + A_6)\,X_r + (A_7X_L + A_8Y_L + A_9)\,X^2_r \quad (3)$$

Where (X_r, Y_r) are the pixel coordinates in the QuickBird data and $A_{1\text{-}9}$ are unknown parameters. Using Equation 3, the quasi-epipolar image pair can be generated by re-arranging the original QuickBird image pair. However, the computation of the unknown parameters of any epipolar geometry needs a certain number of well-distributed conjugate points.

Sum of square difference matching algorithm

Sum of square difference was another matching technique where matching was done pixel-by-pixel or in other word, pixel-based matching (Figure 3). The concept of 'sum of square difference matching algorithm' is implemented left and right images (Figure 2). A template with suitable size was moved in the search window to locate and match its conjugate points. The size of the searching window must be larger than the template window (Sun, 2002). Figure 3 shows that the template with suitable size must be smaller than the size of the search window (for example, template of 3 × 3 and search window of 7 × 7 pixels and lines). To obtain best correlation value, rectification of the images must be at high accuracy (Sun, 2002). The 'sum square of the difference' range is between 0 until 1. If the value was 1, it indicates that the difference between the pixels is high. Therefore, the least value of SSD indicates less difference between the 2 pixels and indicates a better match. The equation for SSD matching algorithm can be expressed as;

$$SSD \equiv \sum \left(f_o(x + j) - f_i(x + j + d_{(i)}) \right)^2 \quad (4)$$

Where SSD is 'sum of square difference' value, f_o is

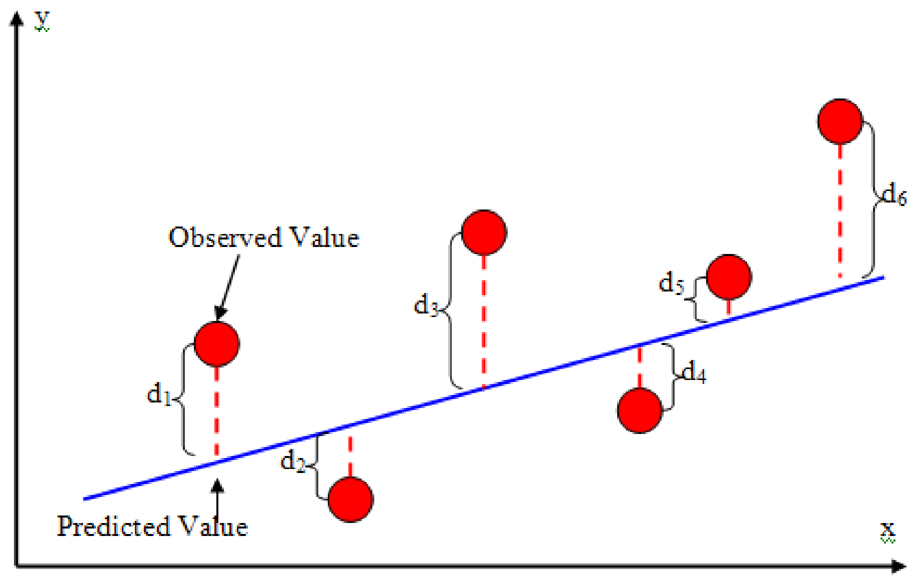

Figure 4. Determine best fit of data points.

template Grey-level matrix; f_i is search window in Grey-level matrix, x is height of template and j is width of template. The 'sum of square difference' is applied to determine the difference of data observed with the data tested. This was because the residual errors obtained from point selected could be calculated to determine the best fit. Sum square of difference method had become a powerful tool in image matching (Gruen, 1985). Not only for determination of difference of points, the SSD method was capable of extinguishing the correlation between both data. The basic equation of 'least square' could be determined in Equation 4.

Determination of best fit data

The matching of pixels could be expressed and be calculated to determine the best fit so that matching can be more precise. Points are tested to determine the best fit which must obtain the least or minimum values to indicate the points have been strongly matched. Figure 4 shows that the relationship of points could be well explained. The closer the points to the line, the fit of the matched points were stronger and better prediction could be obtained. Compared to points that were away from the line, matches were not perfect. The residual error could be calculated by using the equation stated:

$$r = (P - P') \tag{5}$$

Where r is residual error, P is observed points (that is seed points in image 1) and P' is tested points (seed points in image 2). The calculation of the residual error is done to every matched pixel to determine the fit. Not all pixels that were to be matched perfectly and occurred to mismatch. The least residual error (r) calculated from the matched points indicates accurately matching. The range of residual errors must be close to 0 to indicate strong correlations. Matching accuracy is done based on the root mean square error (RMSE). Accurate matching must have value of RMSE which is close to 0:

$$RMSE = \frac{\sqrt{(X - X')^2}}{N - 1} \tag{6}$$

Where RMSE is root mean square error, X is pixel value in template, X' is pixel value in search window, N is the pixel numbers. In this study, the matching template sizes of 3 × 3, 5 × 5, and 7 × 7 pixels and lines are examined.

RESULTS

Figure 5 shows the results of first and second matching procedures. Figure 6 indicates that template size of 7 × 7 pixels and lines has accurately performance than template sizes of 3 × 3 and 5 × 5 pixels and lines. This is shown by smaller RMSE value of 8.51. Although the correlation for template 5 × 5 is the highest, it could be determined that the matching of pixels are not established as matching using template 7 × 7 pixels and lines. Figure 7 confirms that the template size of 7 × 7 provides lower RMSE value of 8.3 compared to first matching procedure. Template size of 7 × 7 pixels and lines for first and second matching procedures have correlation value of 0.82 and 0.83 which shows high level of correlation. First and second matching procedures

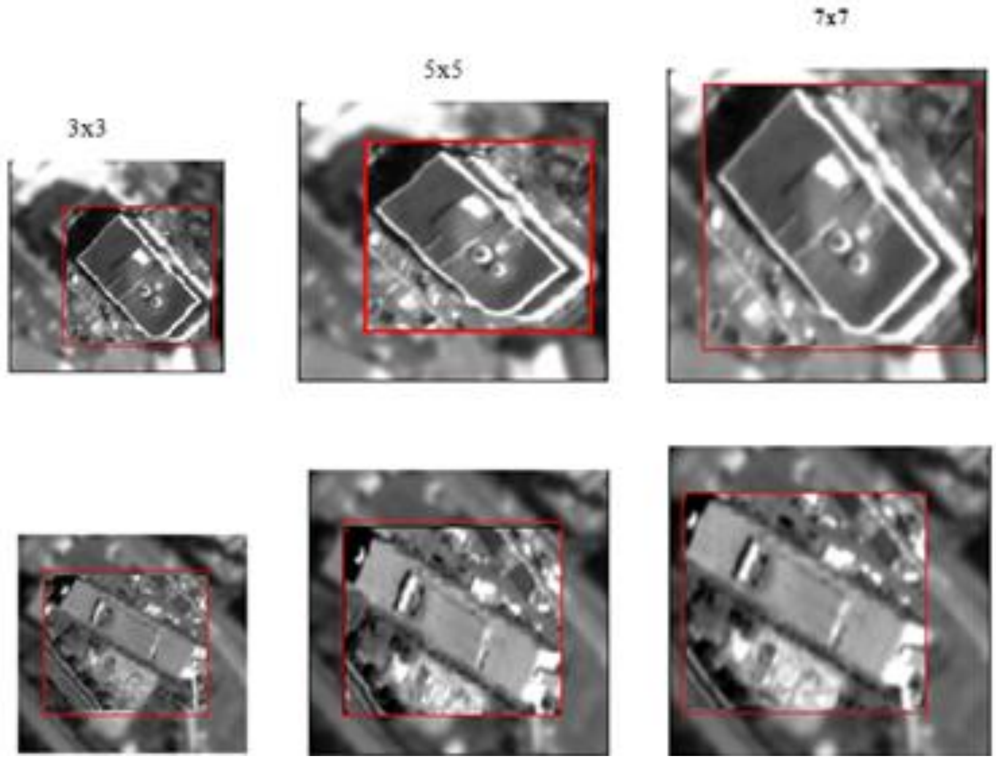

Figure 5. Results of first and second matching procedures.

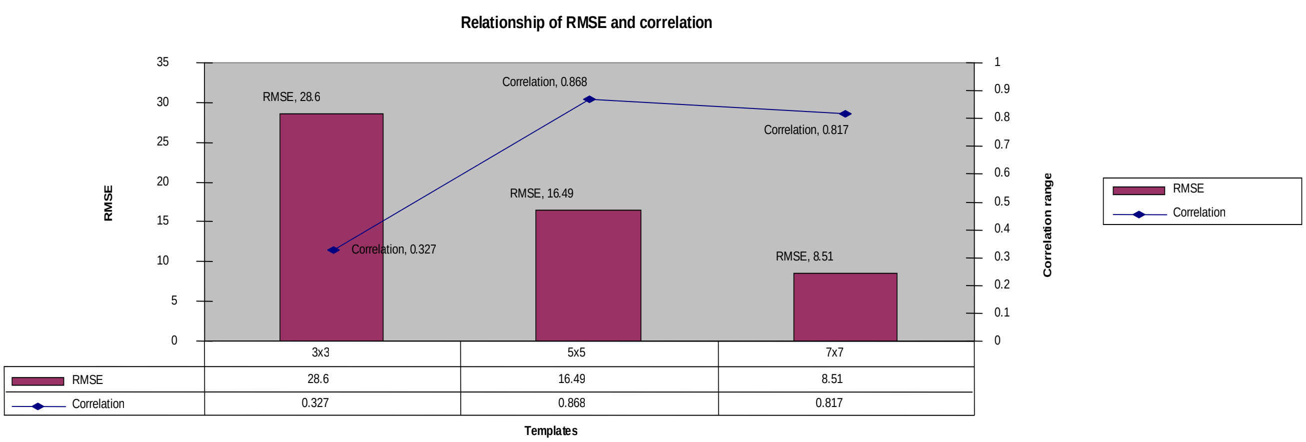

Figure 6. First matching procedure using template sizes of 3 × 3, 5 × 5 and 7 × 7 pixels and lines.

have a lower value of RMSE of 8.51 and 8.33 pixels, respectively (Figures 6 and 7). Successful matched and unmatched is also determined where the first and second matching procedures have a percentage value of 72 and 76% matched of pixels. Figures 6 and 7 shows that unmatched of pixels for first and second matching procedures having a percentage value of 28 and 24% respectively. The least of shifting in *X* and *Y* positions indicated that template size of 7 × 7 had been perfectly matched. Further, shifting in *X* and *Y* positions for first and second matching procedures have value of 1.6014 in *X* position and 0.2003 in *Y* position.

DISCUSSION

The main problem that has been raised up during image matching was creating the template, searching for the

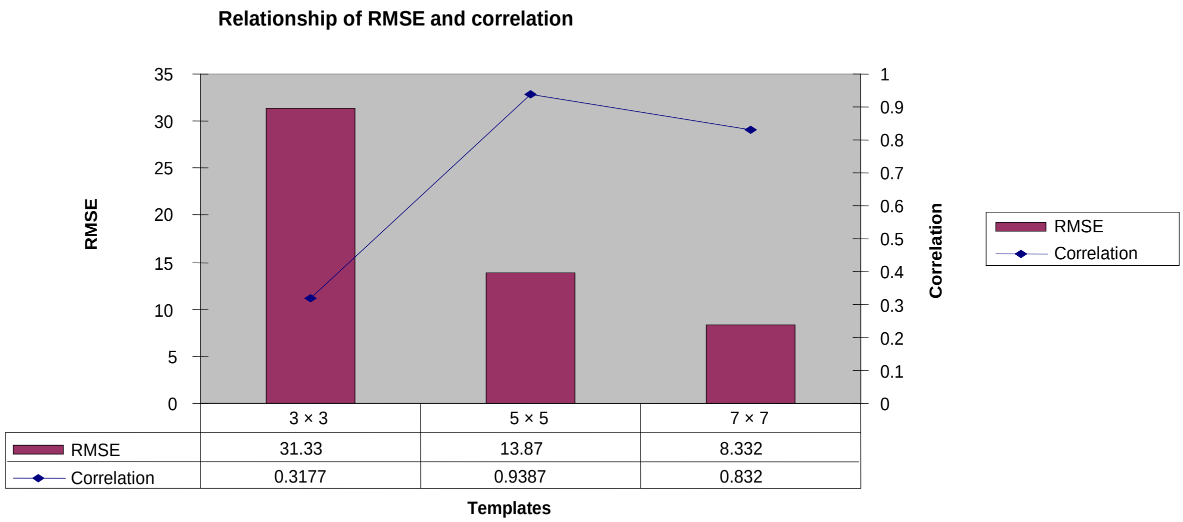

Figure 7. Second matching procedure using template sizes of 3 × 3, 5 × 5 and 7 × 7 pixels and lines.

matching pixels and the correlation between a template and search windows because of algorithm limitations. This can overcome by using a different method such as deform able template model which is based on the fuzzy alignment algorithm (FAA). It provides updating the point correspondence and incorporating the affine-invariant constraints of deformable template. The performance for object matching is greatly improved. Additionally, using the snake algorithm to identify the area in image, which has been matched to discriminate between matched and unmatched areas in images. In fact, this can be used as method to determine the level of matching accuracy with integration of statistical tools. Finally, the match algorithm used in this study can be improved to reconstruct 3-D of interesting object in remote sensing image. Clearly, the template size has tremendous role in achieving accurately matching procedure. It shows that template size of 7 × 7 pixels and lines has higher performance with less RMSE than other template sizes. Indeed, the template matching methods determine the similarity between template windows in two images. Acquiring an excellent matching between pixels, identification or convolution must be carried out to avoid noise impact on areas based matching. This agrees with studies of Blake et al. (1994) and Karabork et al. (2002).

By using the template 7 × 7 pixels and lines, it intended to correlate and find its conjugate pixels in the search window with a high correlation value, with less shifting in *X* and *Y* positions. This produces lower RMSE value and less variation between the template and search window. According to Karabork et al. (2002), the SSD (correlation) values obtained between pixels or patches must be close to 1 to show accurate matching. It is hard to determine which size of template is good to perform image matching with a less value of SSD. To examine the matching of pixels, the only way is to perform shifting of template in the search window. The shifting of template is good indicator for accurate correlation value. These results confirm the studies done by Kanade and Okutomi (1994), Candocia and Adjouadi (1997), Thayananthan et al. (2004), Dare (2002) and Karabork et al. (2002). In general, SSD matching algorithm is function of ‘template’ from the left image and ‘search window’ from the right stereo images. According to Shahrudin (2001), template with selected kernel size is used to search for its conjugate value in the search window. Under this circumstance, the size of kernel window of 3 × 3 pixels and lines is too small and it does not cover enough intensity variation while kernel window of 7 × 7 pixels and lines is appropriate to involve an adequate amount of intensity variation for reliable matching.

Conclusions

It was demonstrated that a method for image matching based on SSD algorithm was able to produce accurate results. This method has been tested on Quickbird images with different template sizes of 3 × 3, 5 × 5 and 7 × 7. The most important conclusion that had been derived from the study: template size of 7 × 7 for first and second matching procedure have correlation value of 0.82 and 0.83 which shows high level of correlation. First and second matching procedures have a lower value of RMSE of 8.51 and 8.33 pixels respectively. Successful matched and unmatched was also determined in this study where the first and second matching procedure have a percentage value of 72 and 76% matched of pixels. By using the template 7 × 7, it intended to correlate and find its conjugate pixels in the search window with a high correlation value, least shifting in X and Y positions, least RMSE value and less variation between the template and search window. Unmatched of pixels for first and second matching procedures have a percentage value of 28 and 24% respectively. The least of shifting in X and Y positions indicated that template size of 7 × 7 had been perfectly match.

From the results of matching, it could be summarized that shifting in X and Y positions for first and second matching procedures having values of delta x is 1.6014, delta y is -1.1172 and delta x is 0.8189 and delta y is 0.2003. It could be said that template size of 7 × 7 for SSD algorithm is most appropriate for matching technique.

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