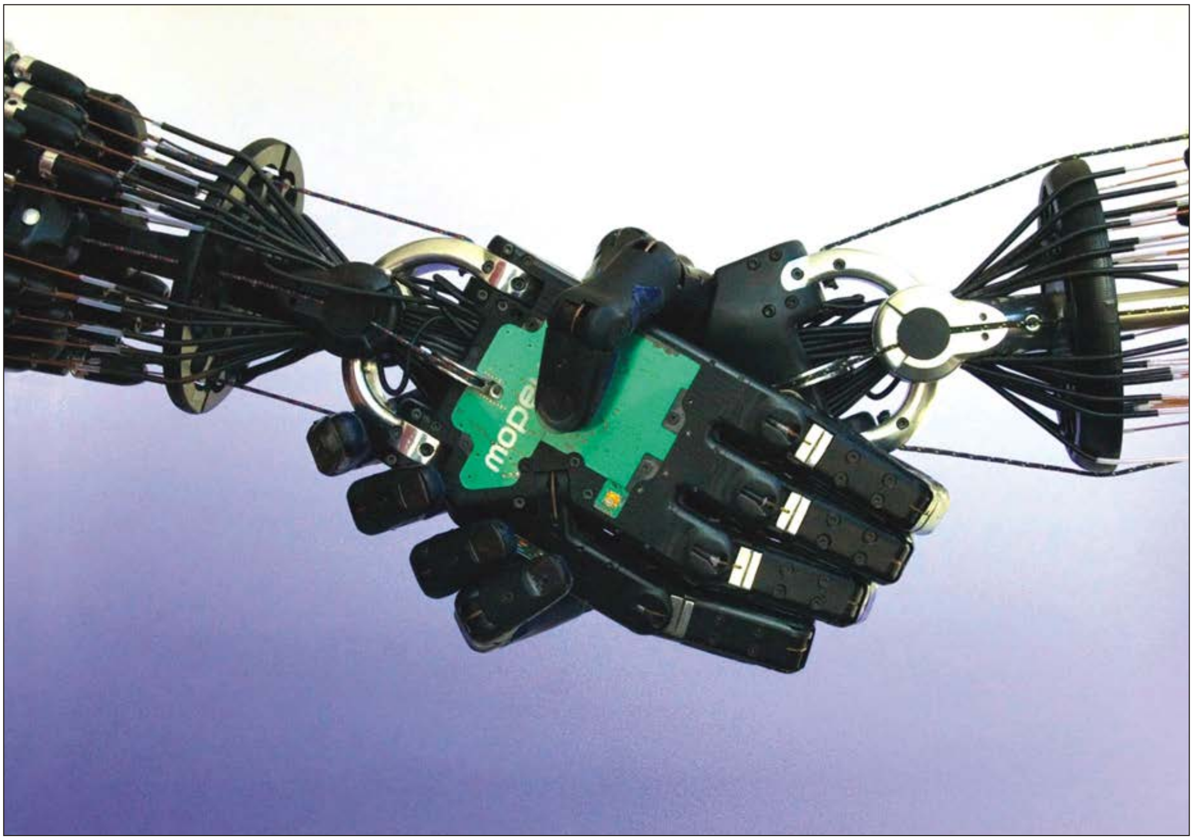

Journal of Artificial Intelligence

ISSN 1994-5450

science alert

ANSInet
an open access publisher
http://ansinet.com

Journal of Artificial Intelligence 5 (3): 122-129, 2012
ISSN 1994-5450 / DOI: 10.3923/jai.2012.122.129

Efficient Cellular Automata Algorithm for Template Matching

Fawaz Alsaade, Yasser Fouda and Abdul Raouf Khan
College of Computer Sciences and Information Technology, King Faisal University, P.O. Box 400, Al-Ahsa 31982, Kingdom of Saudi Arabia

Corresponding Author: Fawaz Alsaade, College of Computer Sciences and Information Technology, King Faisal University, P.O. Box 400, Al-Ahsa 31982, Kingdom of Saudi Arabia

ABSTRACT

Template matching plays an important role in the field of Artificial Intelligence (AI) and it has been used in many applications related to computer vision and image processing such as object recognition and industrial inspection. The main objective of this study was to introduce an appropriate template matching algorithm to enhance the performance of template matching system. The investigation was based on using Cellular Automata with Rule 170 (CA-R170). The main idea of the proposed technique was based on eliminating some of the undesirable area in the binary source images and their corresponding binary template images. The experimental investigations used two sets of color and gray scale images with different sizes and illumination. Experimental results showed that the proposed method can significantly improve the accuracy and execution time of template matching system.

Key words: Template matching system, object recognition, cellular automata, accuracy, execution time, color, gray scale

INTRODUCTION

Process of locating the position of a given pattern in an image is known as template matching. However, template matching is one of the basic approaches for determining the region of interest (Goshtasby *et al.*, 1984). In template matching technique, the position of a given pattern is located by a pixel-wise comparison of the source image with a given template which contains the desired pattern. Previously many investigators developed different well known algorithms such as Normalized Cross Correlation (NCC), Sum of Absolute Difference (SAD), the Sum of Squared Differences (SSD) and image Pyramid in conjunction with Sum of Absolute Difference (PSAD) similarity measure to calculate the comparison among different algorithms (Zhu and Ma, 2000; Li *et al.*, 1994; Po and Ma, 1996; Li and Salari, 1995; Gao *et al.*, 2000; MacLean and Tsotsos, 2000; Lee and Chin, 1997; Alsaade, 2012; Dawoud *et al.*, 2011). Recently, Fu and Liao (2011) proposed a projection transform of wavelet coefficient based multi resolution data-structure algorithm for faster template matching which reduced the number of computation by around 70% over multi resolution data structure algorithm. Zitova and Flusser (2003) concluded that NCC measure is more efficient when compared to SAD and SSD under uniform illumination changes and is used in object recognition and industrial inspection. Lewis (1995) observed that NCC was computationally slow and used to compute the numerator and denominator of its algorithm. Recently, Wei and Lai (2008) proposed a fast pattern matching algorithm based on NCC which was accomplished by combining adaptive multilevel partition with the winner update scheme to achieve very efficient search. Many researchers reported that SAD and SSD were computationally fast particularly when compared to NCC (Barnea and Silverman, 1972; Hayashi and Kadosaki, 2010). Sebe *et al.* (2000) demonstrated that SSD is justified when the additive noise distribution is Gaussian. Hel-Or and Hel-Or (2005) proposed a fast template matching method based on accumulating the distortion on the Walsh-Hadamard domain in the order of the associated frequency using SSD. More recently, Alsaade (2012) has proposed image Pyramid in conjunction with Sum of Absolute Difference similarity measure (PSAD) for template matching. The PSAD algorithm consistently outperformed the execution time offered by NCC and SAD template matching algorithms. The experimental results showed that PSAD algorithm can also obtain accurate matching location results even with noise presence. The main objective of this study was to investigate and propose approach to enhance the performance of template matching system using a cellular automata with rule 170.

MATERIALS AND METHODS

A template matching system involves two stages of operation. The first stage is the model registration to store an image in the computer memory. Whereas, the second stage is to search for a given pattern in an image. This paper mainly investigated the latter process of template matching system. The template matching can simply be defined as follows. For example: In a given source image S and a template image T (Fig. 1, 2), where the dimensions of S are both larger than T, output whether S contains a subset image I where I and T are suitably similar in pattern and if such I exists, output the location of I in S. The location of I in S, will be referred to as the location of the closest match and will be defined as the pixel index of the top-left corner of I in S.

In the present study, a cellular automata with rule 170 was proposed to enhance both the accuracy and execution time of template matching system. This was based on converting both the source and template images into binary images and then eliminating some of the undesirable area in these binary images (Eq. 6). The search was then conducted by saving the coordinates of only

Fig. 1(a-b): Greens, peppers and pills etc. images: set of (a) Color source images containing the template patterns and (b) Their template images

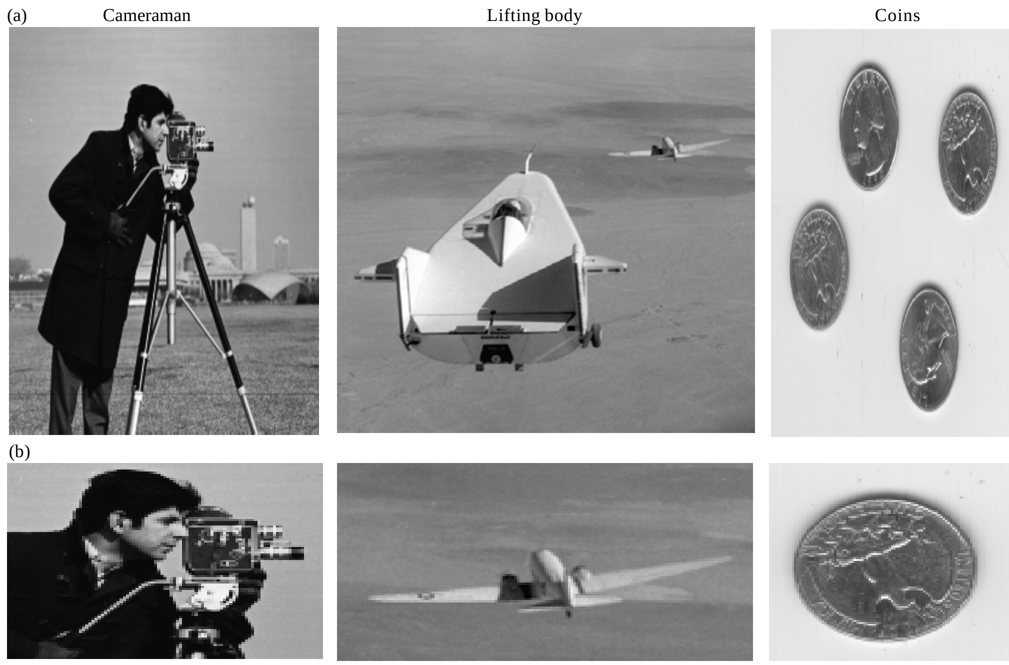

Fig. 2(a-b): Cameraman, lifting body and coins images: set of (a) Gray-level source images containing the template patterns and (b) Their template images

pixels with value 1 in the template image. These coordinates were then used to compare the values of the current block of source image with the template image. The proposed approach was named as Cellular Automata with Rule 170 (CA-R170).

NCC-algorithm: The NCC algorithm computes the likeliness of a match by performing a discrete 2-D correlation of the template image matrix at every possible location in the source image matrix based on the methodologies described by Goshtasby *et al.* (1984), Zitova and Flusser (2003) and Wei and Lai (2008). For example: Let S(x,y) denote the intensity value of the source image of size P×Q at the point (x,y). The pattern was represented by a given template T of the size M×N. A common way to calculate the position (i_{pos}, j_{pos}) of the pattern in the image S was to evaluate the normalized cross correlation value λ(i,j) at each point (i,j) for S and the template T which was shifted by i steps in the x direction and by j steps in the y direction. Basic definition of the Normalized Cross Correlation Coefficient (NCCC) is presented in the following equation:

$$\lambda(i,j) = \frac{\Sigma_{x=0,\,y=0}^{(N-1),\,(M-1)} (S(i+x, j+y) - \bar{S}(i,j))(T(x,y) - T)}{\sqrt{\Sigma_{x=0,\,y=0}^{(N-1),\,(M-1)} (S(i+x, j+y) - \bar{S}(i,j))^2 \, \Sigma_{x=0,\,y=0}^{(N-1),\,(M-1)} (T(x,y) - T)^2}} \tag{1}$$

Where:

$$0 \le i \le (P\text{-}M), 0 \le j \le (Q\text{-}N) \bar{S}(i,j) = \frac{1}{M \times N} \Sigma_{x=0,\,y=0}^{(N-1),(M-1)} \; S(i+x, j+y) \tag{2}$$

$$\overline{T} = \frac{1}{M\times N}\Sigma_{i=0,\, j=0}^{(N-1),\,(M-1)}\ T(i, j) \tag{3}$$

In other words, the highest value of correlation coefficient between the corresponding template and the sub-images inside the source image should determine the correct position for that template. Then, NCC returns (i_{pos}, j_{pos}) as the “closest match” in S. However, it was mentioned that the maximum possible value for $\lambda(i_{pos}, j_{pos})$ is 1.

SAD algorithm: The SAD is a simple algorithm for measuring similarity between the template image T and the sub-images in source image S. It works by taking the absolute difference between each pixel in T and the corresponding pixel in the sub-images being used for comparison in S. These differences are summed to create a simple metric of similarity. For example, let us assume that a 2-D M×N template, T(x,y) is to be matched within a source image S(x,y) of size P×Q where (P>M and Q>N). For each pixel location (x,y) in the image, the SAD distance is calculated according to the procedures given by Barnea and Silverman (1972), Sebe *et al.* (2000), Essannouni *et al.* (2007) and Chen *et al.* (2001) as follows:

$$SAD(x, y) = \Sigma_{k=0}^{(M-1)}\ \Sigma_{l=0}^{(N-1)}\ |S(x+k, y+l) - T(k, l)| \tag{4}$$

In this algorithm, the smaller the distance measured by SAD between the template image T and a sub-image in the source image S, the closer the match is between the searched template and the corresponding sub-image. Therefore, if the measured distance by SAD is zero then the local sub-image is identical to the template.

Cellular automata with rule 170: Wolfram (1983) investigated the CA structure. The study showed that CA structure can be viewed as discrete lattice of sites (cells) where value of each cell can be either 0 or 1. The next state of a cell is assumed to depend on itself and its two neighboring cells for a 3 neighborhood dependency. The cells are evolved in discrete time steps according to some deterministic rule that depends only on local neighborhood. In 2D cellular automata, the cells are arranged in two dimensional grid with connections among the neighborhood cells. The state of CA at any time instant can be represented by an M×N binary matrix. The neighborhood function, specifying the next state of a particular cell of the CA, is affected by the current state of itself and eight cells in its nearest neighborhood. Mathematically, the next state q of the (i,j)th cell of a 2D CA is given by:

$$q_{ij}(t+1) = f\left[q_{i-1,j-1}(t), q_{i-1,j}(t), q_{i-1,j+1}(t), q_{i,j-1}(t), q_{i,j}(t), q_{i,j+1}(t), q_{i+1,j-1}(t), q_{i+1,j}(t), q_{i+1,j+1}\right] \tag{5}$$

where, f is the Boolean function of 9 variables.

To express a transition rule of 2D CA, a specific rule convention according to Khan *et al.* (1997) is presented below:

64	128	256
32	1	2
16	8	4

The central box represents the current cell (that is being considered) and all other boxes represent the eight nearest neighbors of that cell. The number within each box represents the rule number associated with that particular neighbor of the current cell. For example, if the next state of a cell depends only on its present state, it is referred to as rule 1. If the next state of a cell depends on the present state of its right neighbor, it is referred to as rule 2. Similarly, if the next state of a cell depends on the present state of itself top-left cell, it is referred to as rule 64 and so on. In case, the next state of a cell depends on the present state of itself and/or its one or more neighboring cells (including itself), the rule number will be the arithmetic sum of the numbers of relevant cells. For example:

- If the next state of cell depends on the present state of itself and its right neighbor, it is referred to as rule 3 (3 = 1+2)
- If the next state of cell depends on the present state of its right, left and bottom right neighbors, it is referred to as rule 38 (38 = 2+32+4)
- If the next state of cell depends on the present state of itself and its right, bottom, left and top neighbors, it is referred to as rule 171 (171 =1+2+8+32+128)

This study proposed to apply CA with rule 170 to the desired images. The mathematical function representing the next state of the cell with rule 170 is given by the following equation:

$$q_{ij}(t+1) = f\left[q_{i-1,j}(t), q_{i,j-1}(t), q_{i,j+1}(t), q_{i+1,j}(t)\right] \tag{6}$$

In this technique, the targeted source and template images are first converted to binary images and then CA-R170 is applied to the resultant binary images. As mentioned earlier that the searching process in the proposed technique is based on saving the coordinates of only pixels with value 1 in the template image. These coordinates were then used to compare the values of the current block of source image with the template image. Therefore, the proposed approach is expected to enhance the overall performance, time execution and accuracy of the template matching system. This is because the suggested technique aims to reduce the number of 1's in the source and template images (Khan *et al*., 1997; Van Zijl and Botha, 2009).

RESULTS AND DISCUSSION

The present investigation was based on two sets of color and gray scale source images and their template images. Each set consisted of three different images. These images were greens, peppers and pills etc. and cameraman, lifting body and coins as shown in Fig. 1 and 2, respectively. The sizes of these images and their corresponding template matching are illustrated in Table 1. The experiments were performed using Matlab 7.0 on a Laptop with an Intel (R) Core(TM)2 Duo CPU T7500 @ 2.20 GHz and 1.99 GB RAM.

In this study, the process of template matching was based on the use of Normalized Cross Correlation (NCC), Sum of Absolute Difference (SAD) and the proposed approach of Cellular Automata with Rule 170 (CA-R170). Basically, the idea was to determine the level of effective enhancement offered by the proposed method as compared to the most popular template matching approaches. The present research investigated the effect of CA-R170 for enhancing the reliability

Table 1: Sizes of the color and gray scale images and their template matching

Image name	Size of source image	Size of template matching
Greens	512×384	100×100
Peppers	512×384	198×135
Pills etc.	500×300	100×100
Cameraman	256×256	100×90
Lifting body	512×512	170×90
Coins	242×308	100×100

Table 2: Execution time of applying NCC, SAD and CA-R170 to the color source images and their corresponding templates

	Greens		Peppers		Pills etc.	
Algorithm	Time (sec)	%	Time (sec)	%	Time (sec)	%
NCC	153.78	100.00	400.26	100.00	228.78	100.00
SAD	47.16	30.67	129.20	32.28	73.28	32.03
CA-R170	0.11	0.07	0.73	0.18	0.72	0.31

Table 3: Execution time of applying NCC, SAD and CA-R170 to the gray scale source images and their corresponding templates

	Cameraman		Lifting body		Coins	
Algorithm	Time (sec)	%	Time (sec)	%	Time (sec)	%
NCC	45.48	100.00	425.39	100.00	58.44	100.00
SAD	14.45	31.77	138.59	32.58	17.42	29.81
CA-R170	0.14	0.31	0.23	0.05	0.29	0.49

of template matching system which was on two sets of color and gray scale images. The results of experiments for the execution time (seconds) for the two sets of images (color and gray scale images) are presented in Table 2 and 3.

The study results showed that the use of CA-R170 always lead to the lowest execution time for the color and grey scale images (Table 2, 3). Data in Table 2 showed that the application of CA-R170 algorithm on the green, peppers and pills etc. images (color images) took 7, 18 and 31% execution time, respectively as compared to NCC algorithm when applied on the same images. On the other hand, CA-R170 saved 99.69, 99.95 and 99.51% execution time as compared to NCC algorithm when applied on the cameraman, lifting body and coins images (gray scale images), respectively (Table 3). These findings confirmed the earlier suggestion that the use of CA-R170 can enhance the performance in terms of execution time of the template matching system. This might be due to the capability of CA-R170 to produce the skeleton image for the targeted pattern. In other word, CA-R170 can reduce number of 1's in the source and template images. This in turn can help reduce the processing time especially if the searching process was based only on the saved coordinates of pixels with value 1 in the template image. Also, the accuracy, obtaining the correct position for the templates in their corresponding source images, of CA-R170 algorithm was 100%. This outcome was achieved also by NCC and SAD template matching techniques.

The study results agree with the findings of many researchers who introduced Cellular Automata (CA) in the field of image processing and template matching (Khan *et al*., 1997; Ma *et al*., 2009; Tubbs, 1989). Similarly, De Saint Pierre and Milgram (1992) used two dimensional cellular automata for template matching but its contribution was very little. Also, Van Zijl and Botha (2009) showed that it is possible to simplify the three-dimensional shape extraction problem to a two-dimensional case for the LEGO brick based on the cellular automata feature extraction. The study findings also coincides with those of Tubbs (1989) who proposed some generalizations of binary template matching procedures which enables one to weight matches according to both statistical and spatial information.

CONCLUSIONS

This study investigated the use of Cellular Automata (CA) with Rule 170 (CA-R170) for template matching systems based on the use of two sets of color and gray scale source images and their template images. The CA-R170 was compared with two most popular template matching approaches NCC and SAD. Amongst these template matching methods, CA-R170 appeared to provide the best performance in terms of reducing the execution time required for locating the position of a region of interest in an image. The reason for this seems to be the ability of CA-R170 to reduce number of 1's in the source and template images. This in turn would help reduce the processing time especially when the searching process is based only on the saved coordinates of pixels with value 1 in the template image. Additionally, the experimental results showed that CA-R170 algorithm can also obtain accurate matching location results with 100% accuracy.

REFERENCES

Alsaade, F., 2012. Fast and accurate template matching algorithm based on image pyramid and sum of absolute difference similarity measure. Res. J. Inf. Technol., 4: 204-211.

Barnea, D.I. and H.F. Silverman, 1972. A class of algorithms for fast digital image registration. IEEE Trans. Comput., C-21: 179-186.

Chen, Y.S., Y.P. Huang and C.S. Fuh, 2001. A fast block matching algorithm based on the winner-update strategy. IEEE Trans. Image Proces., 10: 1212-1222.

Dawoud, N.N., B.B. Samir and J. Janier, 2011. Fast template matching method based optimized sum of absolute difference algorithm for face localization. Int. J. Comput. Appl., 18: 30-34.

De Saint Pierre, T. and M. Milgram, 1992. New and efficient cellular algorithms for image processing. CVGIP: Image Understanding, 55: 261-274.

Essannouni, F., R.O.H. Thami, D. Aboutajdine and A. Salam, 2007. Adjustable SAD matching algorithm using frequency domain. J. Real-Time Image Proces., 1: 257-265.

Fu, X.P. and S.L. Liao, 2011. A fast template matching algorithm based on wavelet coefficient projection transform. Applied Mechanics Materials, 48-49: 21-24.

Gao, X.Q., C.J. Duanmu and C.R. Zou, 2000. A multilevel successive elimination algorithm for block matching motion estimation. IEEE Trans. Image Process., 9: 501-504.

Goshtasby, A., S.H. Gage and J.F. Bartholic, 1984. A two-stage cross correlation approach to template matching. IEEE Trans. Pattern Anal. Machine Intell., 6: 374-378.

Hayashi, T. and Y. Kadosaki, 2010. Fast and accurate template matching with silhouette masking. Proceedings of the 2010 IEEE/ACIS 9th International Conference on Computer and Information Science, August 18-20, 2010, Yamagata, pp: 258-263.

Hel-Or, Y. and H. Hel-Or, 2005. Real-time pattern matching using projection kernels. IEEE Trans. PAMI, 27: 1430-1445.

Khan, A.R., P.P. Choudhury, K. Dihidar, S. Mitra and P. Sarkar, 1997. VLSI architecture of a cellular automata machine. Inter. J. Comput. Math. Appl., 33: 79-94.

Lee, C.H. and L.H. Chen, 1997. A fast motion estimation algorithm based on the block sum pyramid. IEEE Trans. Image Process., 6: 1587-1591.

Lewis, J.P., 1995. Fast template matching. Proceedings of the Processing and Pattern Recognition Society, May 15-19, 1995, Quebec City, Canada, pp: 120-123.

Li, R., B. Zeng and M.L. Liou, 1994. A new three-step search algorithm for block motion estimation. IEEE Trans. Circuits Syst. Video Technol., 4: 438-442.

Li, W. and E. Salari, 1995. Successive elimination algorithm for motion estimation. IEEE Trans. Image Process., 4: 105-107.

Ma, L., Y. Sun, N. Feng and Z. Liu, 2009. Image fast template matching algorithm based on projection and sequential similarity detecting. Proceedings of the 5th International Conference on Intelligent Information Hiding and Multimedia Signal Processing, September 12-14, 2009, Kyoto, Japan, pp: 957-960.

MacLean, J. and J. Tsotsos, 2000. Fast pattern recognition using gradient-descent search in an image pyramid. Proc. Int. Conf. Pattern Recog., 2: 873-877.

Po, L.M. and W.C. Ma, 1996. A novel four-step search algorithm for fast block motion estimation. IEEE Trans. Circ. Syst. Video Technol., 6: 313-317.

Sebe, N., M.S. Lew and D.P. Huijsmans, 2000. Toward improved ranking metrics. IEEE Trans. Pattern Anal. Mach. Intell., 22: 1132-1143.

Tubbs, J.D., 1989. A note on binary template matching. Pattern Recognit., 22: 359-365.

Van Zijl, L. and L. Botha, 2009. Feature extraction for image pattern matching with cellular automata. Proceedings of the Prague Stringology Conference, Vol: 12, August 31-September 2, 2009, South Africa, pp: 3-14.

Wei, S.D. and S.H. Lai, 2008. Fast template matching based on normalized cross correlation with adaptive multilevel winner update. IEEE Trans. Image Process., 17: 2227-2235.

Wolfram, S., 1983. Statistical mechanics of cellular automata. Rev. Mod. Physics., 55: 601-644.

Zhu, S. and K.K. Ma, 2000. A new diamond search algorithm for fast block-matching motion estimation. IEEE Trans. Image Process., 9: 287-290.

Zitova, B. and J. Flusser, 2003. Image registration methods: A survey. Image Vision Comput., 21: 977-1000.