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Normalize Cross Correlation Algorithm in Pattern Matching Based on 1-D Information Vector

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ABSTRACT

All previous published study in pattern matching based on normalized cross correlation worked in 2-D image. In this study, we propose a pattern matching algorithm using 1-D information vector. The proposed algorithm consists of three main steps: First, the pattern image is scanned in two directions to convert the pattern image from 2-D image into 1-D information vector. Secondly, all blocks (having same size of pattern) in the reference image also are scanned in two directions to obtain 1-D information vector for each block in the reference image. Thirdly, the normalized cross correlation between 1-D information vector of pattern image and all 1-D information vectors in the reference images are established. Finally, we can determine the correct position of pattern in the reference image. Experimentally, we compared the proposed algorithm with three 2-D pattern matching algorithms. The results shown that, the proposed algorithm is more efficient and outperforms the others. Also, we examined the proposed under three different types of noise and we found that it is very robust against noise.

Key words: Image processing, pattern matching, NCC, 1-D information vector

INTRODUCTION

Pattern matching is a basic technique in many branches in image processing and computer vision. Applications in image processing include for example, image recognition (Peng *et al*., 2003), image retrieval (Del Bimbo and Pala, 1997) and registration of images (Bentoutou *et al*., 2005). Applications in computer vision include for example, stereo vision (Di Stefano *et al*., 2005; Olson, 2002), 3-D reconstruction (Takita *et al*., 2004), object tracking (Jurie and Dhome, 2001) and medical imaging (Sussman and Wright, 2003). The problem statement can be simplified as following: we have a reference image include many objects and a pattern for one of these objects we want to search this pattern in the reference image. Many methods were introduced to solve this problem such as Sum of Square Difference (SSD), Sum of Absolute Difference (SAD) and Normalized Cross Correlation (NCC). The mathematical properties of SSD and SAD is not difficult and very efficient computationally see (Ouyang *et al*., 2012; Alsaade and Fouda, 2012). However, SSD and SAD are sensitive to additive noise and changes of illumination. So, these two methods can be used in video compression applications, such as block motion estimation (Li *et al*., 1994). The mathematical formula for SSD and SAD functions at location (u, v) in the reference image R is given by:

$$\mathrm{SSD}(u,v)=\sum_{s=1}^{n}\sum_{t=1}^{m}\left(R(u+s,v+t)-P(s,t)\right)^{2} \tag{1}$$

$$\mathrm{SAD}(u,v)=\sum_{s=1}^{n}\sum_{t=1}^{m}\left|R(u+s,v+t)-P(s,t)\right| \tag{2}$$

where, P is the pattern image of size m×n.

Beside SSD and SAD there is NCC method which is more robust to noise but it is computationally expensive. In NCC the normalize cross correlation λ(u,v) between pattern P and blocks in the reference image is given by:

$$\lambda(u,v)=\frac{\sum_{s=1}^{n}\sum_{t=1}^{m}\left(R(u+s,v+t)-\overline{R}(u,v)\right)\left(P(s,t)-\overline{P}\right)}{\sqrt{\sum_{s=1}^{n}\sum_{t=1}^{m}\left(R(u+s,v+t)-\overline{R}(u,v)\right)^{2}\sum_{s=1}^{n}\sum_{t=1}^{m}\left(P(s,t)-\overline{P}\right)^{2}}},\ 1\le u<(p-m),\ 1\le v<(q-n) \tag{3}$$

Where:

$$\overline{R}(u,v)=\frac{1}{m\times n}\sum_{s=1}^{n}\sum_{t=1}^{m}R(u+s,v+t)\quad\text{and}\quad\overline{P}=\frac{1}{m\times n}\sum_{s=1}^{n}\sum_{t=1}^{m}P(s,t) \tag{4}$$

where, R(x,y) is the gray scale value of a reference image of size p×q at location (x,y) and $\overline{R}$(u,v) is the mean of a block in the reference image have a size m×n with left up corner (u,v). Also P(s,t) is the gray scale of the pattern image at location (s,t) and $\overline{P}$ is the mean of the pattern image. The values of λ (u,v) is between -1 and 1 the location $(\hat{u},\hat{v})$ at which λ(u,v) is maximum is the true position for the pattern P in the reference image R.

Several methods have been proposed for develop pattern matching using NCC. The Coarse-To-Fine (CTF) technique is a well-known method in the pattern matching based on NCC strategy to reduce the computational cost. This technique creates a series of low-resolution images for both pattern and reference images. The search is to conduct with the most coarse pattern in the most coarse reference image. The resulting pixel location provides a coarse location of the pattern in the next lower level of the reference image. Therefore, instead of performing a complete search in the next level, one requires to only search a close vicinity of the area computed from the previous search. This sequence is iterated until the search in the reference image is searched. Lee and Chen (1997) introduced an algorithm use the block sum pyramid to eliminate unnecessary search positions. First they construct the sum pyramid structure of a block. Then a successive elimination is performed from the top to the bottom level of the pyramid. Many search positions can be skipped from being considered as the best motion vector and thus the search complexity can be reduced.

Di Stefano and Mattoccia (2003), Di Stefano *et al*. (2005) and Mattoccia *et al*. (2008) estimated an upper bound of the similarity and eliminated unnecessary calculations to accelerate the pattern matching. In the matching process they checked at each search position a suitable elimination condition depending on the evaluation of an upper-bound for the NCC function based on Cauchy-Schwarz inequality. This check allowed a rapid skipping the positions that cannot provide a better degree of match with respect to the current best-matching one. Wei and Lai (2008) proposed a pattern matching algorithm based on NCC by combining the winner update scheme with adaptive multilevel partition. They applied winner update scheme in conjunction with an upper bound for cross correlation derived from Cauchy-Schwarz inequality. They partition the summation of cross correlation into different levels with the partition order determined by the gradient energies of the partitioned regions in the pattern. Thus this winner update scheme with upper bound for NCC can be helped to skip unnecessary calculations. Gharavi-Alkhansari (2001) combined CTF strategy with the upper bound of similarity strategy and proposed a technique for estimating a threshold in the coarse search and pruning the candidates in the fine search.

Reducing data in the image by converting the image from 2-D into 1-D is a new strategy in pattern matching introduced by Lin and Chen (2008). He used ring projection transform to move the 2-D pattern in a circular region into a 1-D gray scale signal depending on the radius. Fouda (2014) convert the 2-D images into 1-D vector information by summing-up the intensity values in all rows in the vertical direction. He used the SSD function in the matching process, so his method was sensitive to noise. In this study, we developed the 1-D pattern matching algorithm proposed by Fouda (2014) to make the pattern matching process robust against to noise and more efficient. Instead of the image scanned in one direction, we scan the image in two directions to increase the features in the 1-D information vector. Then the matching process can be done under large degree of noise. Also, the Normalized Correlation Coefficient (NCC) between 1-D information vectors are established instead of SSD function. The remainder of the paper is organized as follows. The next section describe the proposed method and outline the whole algorithm and its complexity. Simulation and comparison results for the proposed algorithm with NCC, SAD and Coarse-To-Fine (CTF) standard are reported in results and discussion section. Then we state conclusions.

MATERIALS AND METHODS

First we formalize the pattern matching problem in simple form: Given a reference image of size $p \times q$ and a pattern image of size $m \times n$, where $m<p$ and $n<q$ we want to determine the position of a block of size $m \times n$ in the reference image, which is most similar to the pattern image. The basic algorithms of pattern matching are SAD, SSD and NCC. For the SAD and SSD the similarity measure between pattern image and sub-windows image in the reference image are computed and the sub-window with minimum value is the best match for pattern in reference image. But for NCC algorithm the correlation coefficient between the pattern and all sub-windows in the reference image are computed and the sub-window with maximum value is the true solution. The NCC is robust against noise but its computationally expensive, especially when the size of pattern is large. Conversely, the computation of SAD algorithm is not expensive and in the same time it is sensitive to noise, especially at variation of illumination, which occur in many particle problems. These two gaps prompted us to develop our algorithm. The motivation of our technique is reduce the consumed time especially when the size of the pattern image is large. Also, design a new pattern matching technique to be more robust against noise.

The proposed Cross Correlation 1-D algorithm (CC1D) overcomes the sensitive of SAD and expensive computation of NCC by computing the correlation coefficient between pattern and sub-windows using 1-D information vector. The matching process between vectors in 1-D will save a time and using correlation coefficient will make the technique robust against to noise. Moreover, in CC1D we scan the image in two directions to be more robust. The basic idea of CC1D depend on reducing data dimensionality by converting 2-D image into 1-D information vector. First, for the pattern image P of size m×n we construct 1-D vector P_{n+m} to represent the pattern image in the matching process. This 1-D vector P_{n+m} consists of two components P_n and P_m. The first component P_n is computed by scanning the pattern image in vertical direction by summing up the intensity values for each column in the pattern. So, the components of P_n is given by:

$$P_n = \left(\sum_{i=1}^{m} P(i,1), \sum_{i=1}^{m} P(i,2), \sum_{i=1}^{m} P(i,3), \ldots\ldots, \sum_{i=1}^{m} P(i,n) \right) \tag{5}$$

The second component P_m is computed by scanning the pattern image in horizontal direction by summing up the intensity values for each row in the pattern to obtain P_m by:

$$P_m = \begin{pmatrix} \sum_{j=1}^{n} P(1,j) \\ \sum_{j=1}^{n} P(2,j) \\ \vdots \\ \vdots \\ \sum_{j=1}^{n} P(m,j) \end{pmatrix} \tag{6}$$

Now we can construct the 1-D information vector $P_{n+m} = (P_n, P'_m)$ where P'_m is the transpose of P_m, So P_{n+m} is given by:

$$P_{n+m} = \left(\sum_{i=1}^{m} P(i,1), \sum_{i=1}^{m} P(i,2), \ldots\ldots, \sum_{i=1}^{m} P(i,n), \sum_{j=1}^{n} P(1,j), \sum_{j=1}^{n} P(2,j), \ldots\ldots, \sum_{j=1}^{n} P(m,j) \right) \tag{7}$$

We can write P_{n+m} in the form:

$$P_{n+m} = \left(t_1, t_2, \cdots, t_n, t_{n+1}, \cdots, t_{n+m} \right) \tag{8}$$

Where:

$$t_l = \sum_{i=1}^{m} P(i,l) \qquad 1 \le l \le n$$

$$t_k = \sum_{j=1}^{n} P(k-n, j) \qquad n < k \le n+m$$

Next for all m×n blocks in the reference image with size p×q we construct a 1-D information vector for each block as in the above pattern image. Let us define the blocks of size m×n in the reference image to be B(s,t), where, 1≤s≤(p-m) and 1≤t≤ (q-n). For each B(s,t) we construct a 1-D information vector B_{n+m} of size m+n. This 1-D vector consists of two components B_n and B_m. The components of B_n is computed by summing up the intensity values in vertical direction for each column in the block by:

$$B_n(s,t) = \left(\sum_{i=s}^{m+s-1} B(i,t), \sum_{i=s}^{m+s-1} B(i,t+1), \ldots\ldots, \sum_{i=s}^{m+s-1} B(i,n+t-1) \right) \tag{9}$$

The second component B_m is computed by summing up the intensity values in horizontal direction for each row in the block by:

$$B_m(s,t) = \begin{pmatrix} \sum_{j=t}^{n+t-1} B(s,j) \\ \sum_{j=t}^{n+t-1} B(s+1,j) \\ \vdots \\ \vdots \\ \sum_{j=t}^{n+t-1} B(m+s-1,j) \end{pmatrix} \tag{10}$$

Now a 1-D information vector B_{n+m} (s, t) = (B_n, B'_m) represent this block in the matching process where, B'_m is the transpose of B_m. We can do this transformation for all blocks in the reference image to obtain:

$$B_{n+m}(s,t) = \left(\sum_{i=s}^{m+s-1} B(i,t), \sum_{i=s}^{m+s-1} B(i,t+1), \cdots, \sum_{i=s}^{m+s-1} B(i,n+t-1), \sum_{j=t}^{n+t-1} B(s,j), \sum_{j=t}^{n+t-1} B(s+1,j), \ldots, \sum_{j=t}^{n+t-1} B(m+s-1,j) \right) \tag{11}$$

$$\text{for all } 1 \le s \le (p-m) \text{ and } 1 \le t \le (q-n)$$

We can write 1-D information vectors B_{n+m} (s,t) in Eq. 11 in the form:

$$B_{n+m}(s,t) = \left(b_t, b_{t+1}, \cdots, b_{n+t-1}, b_s, b_{s+1}, \cdots, b_{m+s-1}\right) \tag{12}$$

Where:

$$b_u = \sum_{i=s}^{m+s-1} B(i,u) \qquad t \le u \le (n+t-1)$$

$$b_v = \sum_{j=t}^{n+t-1} B(v,j) \qquad s < v \le (m+s-1)$$

Now we have a 1-D information vector of size m+n for the pattern image Eq. 8 and 1-D information vectors of size m+n for each block in the reference image Eq. 12. The correlation coefficient between 1-D pattern vector and each 1-D block vector can be computed by:

$$CC(s,t) = \frac{\sum_{i=1}^{m+n} (b_i - \bar{b})(t_i - \bar{t})}{\sqrt{\sum_{i=1}^{m+n} (b_i - \bar{b})^2 \sum_{i=1}^{m+n} (t_i - \bar{t})^2}} \tag{13}$$

Which can be simplified into:

$$CC(s,t)=\frac{\sum_{i=1}^{m+n} b_i t_i-(m+n)\bar{b}\bar{t}}{\sqrt{\sum_{i=1}^{m+n}(b_i^2-(m+n)\bar{b}^2)\sum_{i=1}^{m+n}(t_i^2-(m+n)\bar{t}^2)}} \tag{14}$$

Where:

$$b_u=\sum_{i=s}^{m+s-1} B(i,u) \qquad t\le u\le (n+t-1)$$

$$b_v=\sum_{j=t}^{n+t-1} B(v,j) \qquad s< v\le (m+s-1)$$

$$\bar{b}=\frac{1}{m+n}\sum_{i=1}^{m+n} b_i \qquad ,\bar{t}=\frac{1}{m+n}\sum_{i=1}^{m+n} t_i$$

The correlation coefficient values are stored in an array CC(s,t), $1\le s\le$ (p-m) and $1\le t\le$ (q-n) and the position $(\hat{s},\hat{t})$ at which the maximum value of CC (s, t) is obtained correspond the left upper corner of the correct match for the pattern P in the reference image. An overall picture of the proposed algorithm is listed as follows:

Now we discuss the computational cost of the proposed method. First the cost of converting the pattern image from 2-D into 1-D can be ignored in CC1D, since for the pattern this need only be done once (Steps 3 and 4) outside the nested loop in Fig. 1). Also, the computational cost of converting the blocks in the reference image (Steps 8 and 9 in Fig. 1) can be ignored because the contribution due to summing the blocks become negligible compared with computing the correlation coefficient between pattern and blocks in step 11 in Fig. 1. So, the complexity of our method depend on Eq. 14 in the nested loop in Fig. 1. Equation 14 have a summations of length (m+n) inside the nested loops of length (p-m)×(q-n). Then the complexity of CC1D is O((m+n)(p-m)(q-n)), where m×n is the size of the pattern and p×q is the size of reference image.

S1: Read the reference image R and determine the pattern image P
S2: Determine size of R, p×q and size of P, m×n
S3: Scan P in vertical direction to find Pn using Eq. 5
S4: Scan P in horizontal direction to compute Pm using Eq. 6
S5: Construct pattern 1-D vector $P_{n+m}=(P_n,P'_m)$ using Eq. 7
S6: for s=1 to (p-m)
S7: for t=1 to (q-n)
S8: Scan a block of size m×n with left upper corner R(s,t) in the vertical direction to compute Bn using Eq. 9
S9: Scan a block of size m×n with left upper corner R(s,t) in the horizontal direction to compute Bm using Eq. 10
S10: Construct a block 1-D vector $B_{n+m}=(B_n+B'_m)$ using Eq. 11
S11: Compute the correlation coefficient between Pn+m and Bn+m using Eq. 14 and stored in matrix CC
S12: end t
S13: end s
S14: Return the coordinate of maximum value in CC

Fig. 1: Outline for the overall CC1D algorithm

RESULTS AND DISCUSSION

In this section, we carry out the experiments to measure the speeding and accuracy of the proposed algorithm as well as comparing the findings with some previous studies, NCC by Wei and Lai (2008), SAD by Li *et al.* (1994) and CTF by Lee and Chen (1997). Theses algorithms were performed in a MATLAB 7.0 on a Laptop with an Intel® CoreTM2 Duo CPU T7500 at 2.20 GHz and 1.99 GB RAM. We used three types of dataset for evaluation. In the first type the patterns are cropped from the reference image, the second type the patterns not cropped from the reference and the third the camera captures the images from different viewpoints. Figure 2a show truck image of size 512×512 which used in the first type of the dataset and its noisy version as the reference image in Fig. 2b. The three objects in the truck image are chosen as a patterns namely Truck1, Truck2 and Truck3 with sizes 70×130, 70×130, 110×219, respectively. To test the robustness of the methods we increase the brightness of these patterns by 50% and namely the new patterns Truck11, Truck22 and truck33. These patterns and its brighter version are shown in Fig. 3. Figure 4 show the TV remote control image of size 500×800 used in the second type of dataset. The image in Fig. 4a is captured under artificial illumination and the image in Fig. 4b is capture by the same camera and the same position only we switch off the artificial illumination. The image in Fig. 4c is the a pattern of size 100×100 taken from the TV remote control image in Fig. 4a and we search it in the darker TV remote control image in Fig. 4a. The last dataset the patterns are extracted from another images taken by the same camera from different viewpoint. These dataset published by Mattoccia *et al*. (2008) which consists of a reference board image of size 480×640 and three patterns of different sizes. The reference board image and the three patterns are shown in Fig. 5.

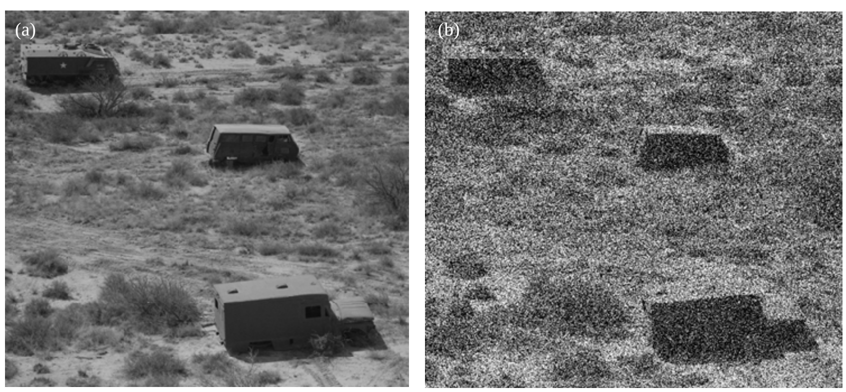

Fig. 2(a-b): Truck image (a) Clean reference image (b) Gaussian noise version with variance 0.1

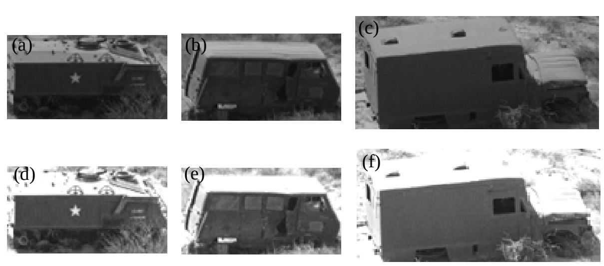

Fig. 3(a-f): (a) Truck1, (b) Truck2 and (c) Truck3 are the three patterns cropped from clean reference image. (d) Truck11, (e) Truck22 and (f) Truck33 are the bright version by 50% for Trcuk1, Truck2, Truck3, respectively

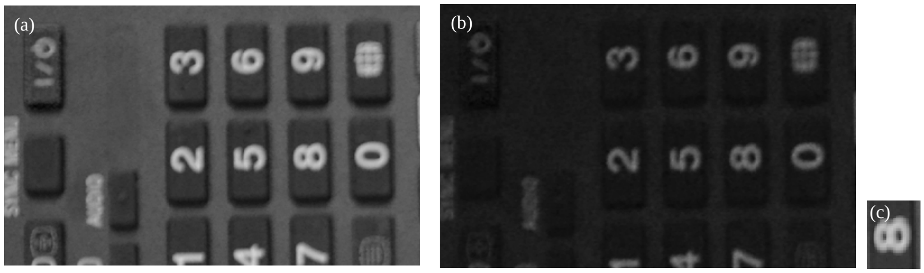

Fig. 4(a-c): TV Remote control image (a) Image capture under artificial illumination (b) Dark version of (a) and (c) Pattern taken from (a)

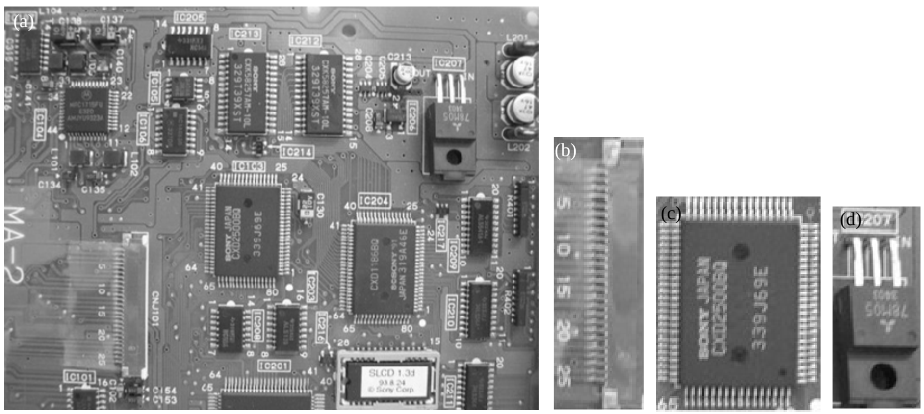

Fig. 5(a-d): (a) Reference board image and the three patterns (b) b1, (c) b2 and (d) b3 taken from three different viewpoints

Patterns cropped from the reference: In this experiment, the truck image and its noise version all of size 512×512 are used as a reference images. The three patterns truck1, truck2 and truck3 and its noise version Truck11, Truck22, Truck33 are used as a patterns to compare the efficiency and robustness of CC1D. Two of these patterns have the same size and the third is different. All patterns are cropped from the clean reference image. The Truck11, Truck22 and Truck33 are the same Truck1, Truck2 and Truck3, respectively but the brightness are increased by 50% (Fig. 3). To check the robustness of CC1D a Gaussian noises with variance 0.1 are added onto the reference image Fig. 2b and a comparison on noise image is occurred. A MATLAB codes were designed for the methods NCC by Wei and Lai (2008), SAD by Li *et al*. (1994), CTF by Lee and Chen (1997) and CC1D and executed on the machine described above. Table 1 and 2 shows the executions times of these methods applied on clean truck and its noise version, respectively.

From Table 1 and 2 we notice that the running time of NCC is very expensive especially when the size of pattern is large as in Truck3 and Truck33. On the other hand NCC is very robust against noise when the Gaussian noise are added to the reference and/or when the brightness are increased to patterns up to 90%. The CTF method give some improvements on NCC on patterns Truck2 and Truck3 and its brightness versions. But the improvement in Truck1 and its brightness version is not significance because the position of this pattern in the reference image is near from the x-axis and y-axis. So, the CTF is efficient when the pattern is far from the two axis. The

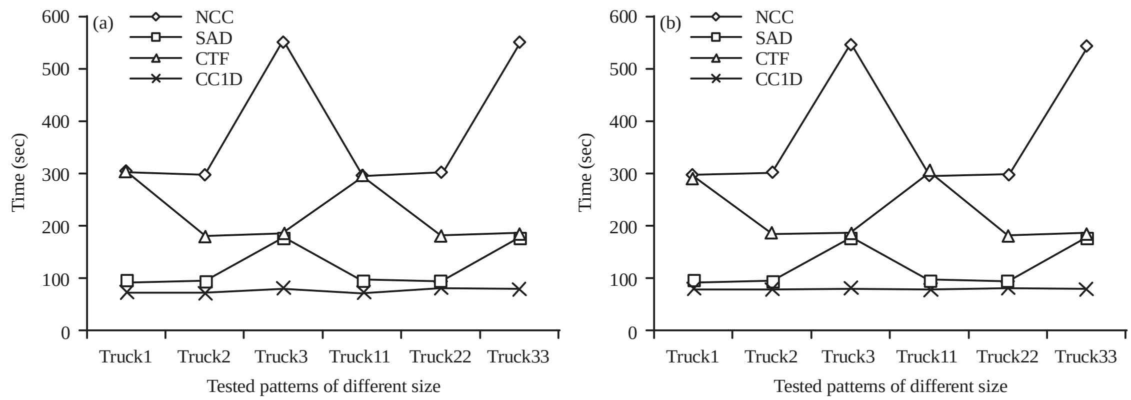

Fig. 6(a-b): Behavior of the discussed methods compared with the proposed on (a) Clear truck image and (a) Noised truck image

Table 1: Running time by second when applying the basic methods and the proposed CC1D to find the six patterns in Fig. 3 from the reference image in Fig. 2a

Seconds	Truck1	Truck2	Truck3	Truck11	Truck22	Truck33
NCC	301.56	296.36	550.53	294.50	301.31	549.72
SAD	94.00	93.51	176.48	93.53	93.65	176.70
CTF	304.05	180.17	185.58	295.36	181.11	185.65
CC1D	70.53	70.34	79.76	70.25	80.89	79.03

Table 2: Running time by second when applying the basic methods and the proposed CC1D to find the six patterns in Fig. 3 from the noised image in Fig. 2b

Seconds	Truck1	Truck2	Truck3	Truck11	Truck22	Truck33
NCC	295.73	301.11	547.22	294.64	296.87	542.33
SAD	93.75	94.20	176.47	93.50	93.36	175.14
CTF	294.45	184.69	185.93	302.12	180.31	185.95
CC1D	78.19	77.87	79.00	77.78	77.65	78.25

running time of SAD is better than NCC and CTF but it gives a false result (indicated by underline in the Table 1 and 2) especially, when the brightness are increased for patterns (36, 39 and 46% for Truck1, Truck2 and Truck3, respectively). Then SAD is sensitive to noise because the basic idea of SAD method depend on the simple absolute difference between gray scale of pixels. Finally the execution time of the proposed is the best compared with all other methods. Because our method convert the 2-D image into 1-D vector with fewer computations. Also our method is robust against noise, we increased the brightness of Truck1, Truck2 and Truck3 up to 71, 56 and 69%, respectively and we founded that the proposed gives a true position for the patterns in the reference. Our method is robust because it depend on computing the correlation coefficient between pattern and sub-windows in the truck image. Another important feature of our proposed, the difference of running time between Truck2 and Truck3 and also between Truck22 and Truck33 is not significant although, the big difference of sizes between these patterns. Figure 6a-b show the behavior of the proposed CC1D compared with other methods on truck image and its noise version, respectively.

Patterns not cropped from the reference: Another way of noise, the pattern is cropped from other scene for the same image with different illumination. We used the TV remote control image of size 500×800 in Fig. 4a. This image captured under artificial illumination using Canon camera. By the same camera and the same position we change the artificial illumination and we take a dark version of the TV remote control image as in Fig. 4b. The pattern surrounded by the white square in Fig. 7a was chosen as the pattern and the image in Fig. 7a is the reference image. Figure 7b

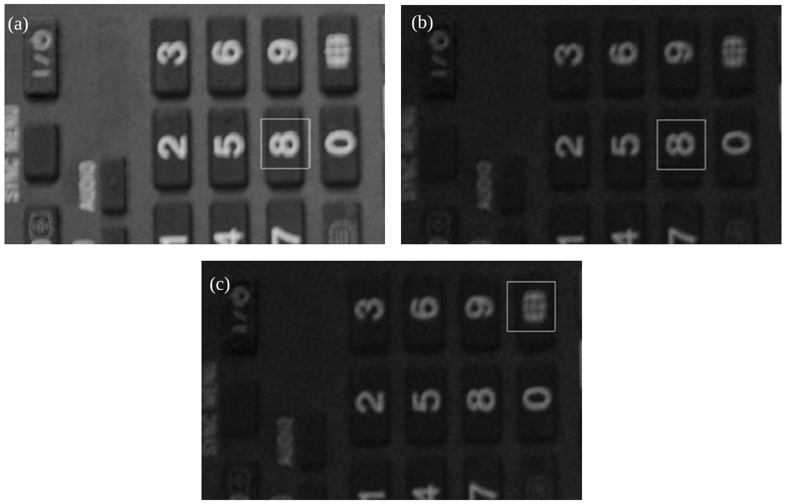

Fig. 7(a-c): (a) Pattern is surrounded by white square, (b) Result of applying CC1D and (c) Result of applying SAD

Table 3: Running time by seconds when applying the basic methods and the proposed CC1D to find the three patterns in Fig. 5 from the board image

Seconds	b1	b2	b3
NCC	383.94	515.23	361.53
SAD	116.76	162.69	111.22
CTF	211.35	306.45	197.98
CC1D	75.45	84.80	90.00

and 7c shows the results when we applied the proposed CC1D and SAD by Li *et al.* (1994), respectively to search the pattern from the reference image. The correct position for pattern was (540,240) in the reference image. When the SAD method was applied it given us (642, 50) as in Fig. 7c. So, SAD method failed to find the correct position of pattern. When the proposed CC1D applied it gives (540, 239) as in Fig. 7b. So, the proposed method is robust against illumination change. The running time for SAD and CC1D was 162.41 and 118.51 sec, respectively and the size of pattern was 100×100.

Patterns from different viewpoints: The noise may be occur in the images when it capture from different viewpoints. Here we use the board image and the three patterns taken from three different viewpoints published in (Mattoccia *et al*., 2008) and available on line in (http://www.vision.deis.unibo.it/smatt/PatternMatching.html). The size of reference board image is mentioned above and the size of the three patterns b1, b2 and b3 are 179×63, 138×106 and 149×65, respectively. These patterns are not cropped from the reference board image itself but from another image taken with the same camera and the same scene from slightly different viewpoints. NCC by Wei and Lai (2008), SAD by Li *et al.* (1994) and CTF by Lee and Chen (1997) are applied to find the positions for the three templates b1, b2 and b3 in the reference board image. All these methods gives a correct positions (113, 265), (239,198) and (500, 61) for b1, b2 and b3, respectively. So, we only compare the running time between these methods. Table 3 shows the running times for NCC, SAD, CTF and CC1D to find the positions of the three patterns from the reference board image.

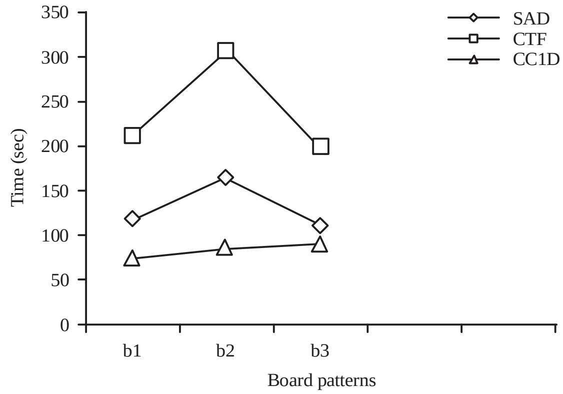

Fig. 8: Performance of the proposed CC1D compared with CTF and SAD on the board image

From Table 3 we notice that the proposed CC1D outperform the other methods, especially when the size of pattern is large as in b2 pattern. The superiority of CC1D, because the computations were transformed from 2-D into 1-D. Also the two algorithms SAD (Li *et al*., 1994) and CTF by Lee and Chen (1997) are outperform NCC algorithm by Wei and Lai (2008). So, it is sufficient to compare the running time of our proposed with SAD and CTF. Figure 8 show the performance of CC1D compared with SAD and CTF when we searched the patterns b1, b2 and b3 in the board image.

CONCLUSION

We have developed a one-dimensional Correlation Coefficient Algorithm (CC1D) for pattern matching. The basic idea of CC1D depend on reducing the complexity of matching process from O(m×n) to O(m+n). So, the computational cost of CC1D is less than 2-D methods in pattern matching for example (NCC, SAD, CTF). The pattern and blocks in reference image are scanned in horizontal and vertical directions to build the (m+n) 1-D information vectors. The correlation coefficient between these 1-D information vectors were used in the matching process. So, CC1D is very robust against noise. We compare CC1D with NCC, SAD and CTF under clean image and image affected by three types of noise. The experimental results shown that CC1D is more efficient than the others and its robust against three types of noise discussed. Suggested future work will use CC1D for defect detection of industrial inspections for example printed-circuit boards.

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