Automatic Target (object) Recognition (ATR) Using Enhanced Versions of Hausdorff Distance

Muhammad Abid Mumtaz
Reg. No.185-FET/MSEE/F08

Department of Electronic Engineering
Faculty of Engineering & and Technology, (FET)
International Islamic University, (IIU), Islamabad

Normalized Cross Correlation

(Acceptance by the Viva Voce Committee)

Title of thesis: Automatic Target (object) Recognition (ATR) Using Enhanced Versions of Hausdorff Distance.

Name of student: Muhammad Abid Mumtaz

Registration No. 185-FET / MSEE / F08

Accepted by the Department of Electronic Engineering INTERNATIONAL ISLAMIC UNIVERSITY, ISLAMABAD, in partial fulfilment of the requirements for the Master of Philosophy Degree in Electronic Engineering with specialization in Image Processing.

Viva voce committee:

Dean
Dr. Ghulam Yasin Chohan
FET.

Chairman
Dr. Muhammad Zubair
DEE, FET.

External Examiner
Dr. Abdul Jalil
Associate Professor, PIEAS.

Internal Examiner
Professor Dr. I.M. Qureshi
DEE, FET.

Supervisor
Dr. Rab Nawaz Chaudhary
Scientist, NDC, NESCOM.

Day, month, year

DECLARATION

I certify that except where due acknowledgments has been made, the work has not been submitted previously, in whole, to qualify for any other academic award, the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program, and any editorial work paid or unpaid, carried out by a third party is acknowledged.

Signed ....Abid Mumtaz.................. (candidate)
Date ....15/09/2012.....

DEDICATION

I dedicate this work done by me to my mother who has stood beside me in the time of troubles as well as in the time of happiness. She devoted her whole life for my future and what I am today is all because of her. I salute her for what she has done for me. Thanks a lot Mom.

ABSTRACT

A novel and robust algorithm to perform image registration for target recognition under partial occlusion is proposed. The algorithm makes use of a particular form of the Normalized Cross Correlation (NCC). The algorithm is able to handle partial occlusion whether it is in the form of randomly located corrupted pixels or as a contiguous block of corrupted pixels. The approach is applicable wherever NCC is used i.e, object detection, biometric (forensics), tracking, stereo matching. The corrupted pixels are detected as a by product of the NCC calculations keeping the computational complexity of our algorithm low. The corrupted pixels are excluded from the NCC calculations in the ranked Hausdorff sense. The algorithm thus performs target (object) recognition by matching certain percentage of the target pixels. Even if the occlusion is coherent, the location of these pixels is not fixed so the algorithm handles occlusion in any part of the target as is the case with ranked Hausdorff algorithm.

ACKNOWLEDGEMENTS

First of all I would like to thank "ALLAH", the most merciful and mighty, who love me 70 times more than my own mother and who gave me this life so that I can learn and spread a message of love and peace in the world. It is ALLAH's blessings that have made me able to complete Master of Science in Electronic Engineering. It is my pleasure to acknowledge and thank people who helped me accomplish my goal to pursue graduate studies. I would like to thank my parents for their constant support and encouragement. They have made lots of sacrifices to help me with my education, for which I will always be grateful. Also I am highly thankful to my beloved siblings who helped me in the time of depression and crises; it would not be possible without their prayers and support because they are always a source of courage for me. I would also like to thank my supervisor and mentor Dr. Rab Nawaz, for his support throughout my graduate research. His willingness to assist whenever needed and his constant words of encouragement and motivation were vital to the completion of this thesis. Also he gave careful and thoughtful feedback, and greatly contributed to the quality of this thesis.

CONTENTS

List of Figures

List of Tables

Chapter 1

INTRODUCTION

1.1 Object recognition

In object recognition a small image (target) (so called template image) is translated over a large image (so called reference image) and a best matching position is found by estimating a similarity/dissimilarity measure.

1.2 Applications

The object/target recognition applications are

- Registering aerial images with the reference images from the satellite imagery.
- Finding a given target in the scene
- A forensic evidence face may also be matched against a list of criminal people.
- A stored face in a watch list may be recognized in a natural scene of people.
- Tracking

1.3 Problems

The problems we face in image registration are due to poor quality of reference and/or template image. The reason is that the two images being taken at different times, different seasons and possibly by different sensors. Another problem is intentional partial occlusion. The reasons could be expression, aging, beard, veil, glasses and camouflage.

1.3.1 Definition of Partial Occlusion

In our thesis by partial occlusion, we mean that a certain percentage of the pixels of the template (or its location in the reference image) is corrupted. These pixels need not be spatially coherent. Different scenarios of partial occlusion are

Gaussian The whole (or portion of) template or the whole (or portion of) location of the template in the reference is degraded by the Gaussian noise.

Salt & Pepper The whole (or portion of) template or the whole (or portion of) location of the template in the reference is degraded by the salt & pepper noise.

constant A portion of template or reference at the template location is occluded completely being set to a high/low constant intensity value.

Reversal A portion of template or reference at the template location is degraded so that intensity is totally reversed at that portion.

1.4 Normalized Cross Correlation

The normalized cross correlation is defined as

$$NCC(u,v) = \frac{\sum(f-\overline{f})(t-\overline{t})}{\sqrt{\sum(f-\overline{f})^2\sum(t-\overline{t})^2}} \tag{1.4.1}$$

Where t is the template image, $\overline{t}$ is its mean, f is the reference image when template image is translated to position (u,v) of the reference image and $\overline{f}$ is its mean. Note that f and $\overline{f}$ will change for all (u,v) locations. It is implicit that the sizes of t and f for one $NCC(u,v)$ calculations are the same. The complexity of NCC is of the order of reference image and the template sizes. Other hardware friendly variants of NCC have been proposed in [3] which use integral images to reduce the computational complexity of NCC. NCC is computed for every (u,v) location and a position with maximum NCC value is declared as a match between template and the reference image. Figure (1.1) shows one such NCC surface. Normalized Cross Correlation (NCC) is a popular measure for image registration under linear changes between the reference and the template images. NCC is sensitive to partial occlusion. Local variations/occlusion degrade the NCC value of the template at its actual position. This leads to match being declared at wrong positions. It also makes NCC surface less peaky, reducing our confidence on the NCC match surface.

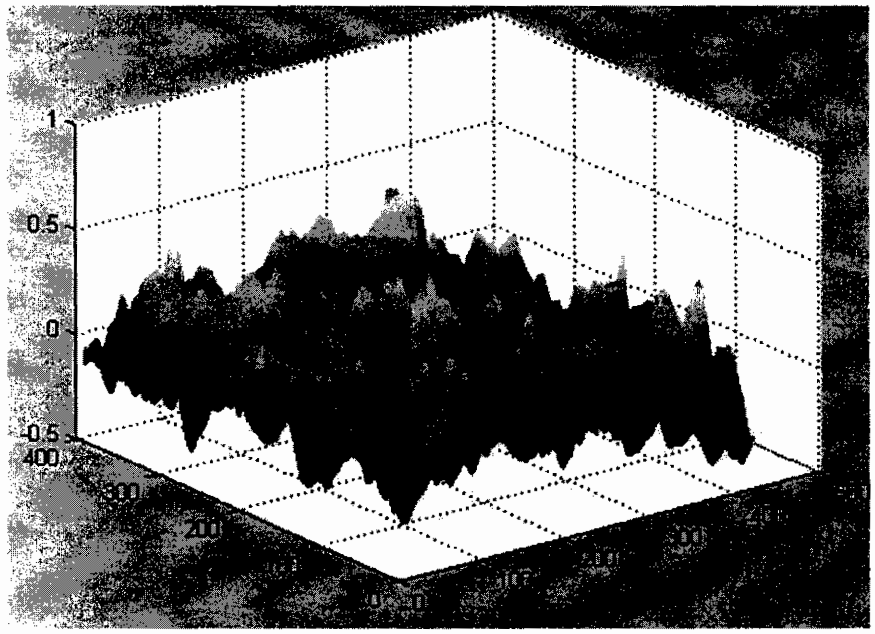

Figure 1.1. NCC surface

1.5 Hausdorff Distance

The Hausdorff Distance (HD) between two finite set points, $A = \{a_1, a_2, ..., a_p\}$ and $B = \{b_1, b_2, ..., b_q\}$ is defined as [4]

$$H(A, B) = max(h(A, B), h(B, A)) \tag{1.5.1}$$

where

$$h(A, B) = max_{a \in A} B_D(a) \tag{1.5.2}$$

similarly

$$h(B, A) = max_{b \in B} A_D(b) \tag{1.5.3}$$

$h(A, B)$ is called the directed Hausdorff Distance from A to B. $h(B, A)$ is called the directed Hausdorff Distance from B to A. $H(A, B)$ is the maximum of these two directed distances. $B_D(a)$ is the DT value of image B at edge locations given by A. $h(A, B)$ gives the distance of the farthest point in A from its nearest point in B. $h(B, A)$ gives the distance of the farthest point in B from its nearest point in A.

The directed distance measures h(A,B) and h(B,A) are sensitive to partial occlusion as they are based on the *max* operator.

Hausdorff Distance (HD) has historically been used in conjunction with edge images. In the context of template matching, edge images of the template and reference images are gotten. Another so called Distance Transform of both the images is also calculated. The distance transform, at every location, measures the distance from the nearest edge. The edge pixels of the template and the corresponding portion of the reference are the elements of the sets A and B. HD surface is estimated by translating the template and estimating HD for all the locations. The template matched position is found by finding the minimum of the HD surface.

The directed distance measures h(A,B) and h(B,A) are sensitive to occlusion as they are based on the *max* operator. The authors in [4] also propose a robust version by defining h(A,B) as below

$$h_L(A, B) = L^{th}_{a \in A} B_D(a) \tag{1.5.4}$$

$h_L(A, B)$ gives L^{th} largest value of B_D at locations given by A. similarly

$$h_K(B, A) = K^{th}_{b \in B} A_D(b) \tag{1.5.5}$$

$h_K(B, A)$ gives K^{th} largest value of A_D at locations given by B. Finally the Partial Hausdorff Distance (PHD) is given as

$$H_{LK}(A, B) = max(h_L(A, B), h_K(B, A)) \tag{1.5.6}$$

The L and K are given as fraction of the total number of edge pixels being matched. For example if want to match only best 75% of the template points given by A, we shall set $L = 0.75 * n_A$, where n_A is the number of edge pixels in set A. If want to match only best 75% of the reference points given by B, we shall set $K = 0.75 * n_B$, where n_B is the number of edge pixels in set B.

The PHD algorithm handles occlusion by matching $max(L, K)$ points on the template. It handles occlusion by comparing only the best portions of the template but is shown to be still sensitive to occlusion due to using a ranked value from the list of distances. To tackle partial occlusion, the authors in [2] propose Modified Hausdorff Distance (MHD) based on the following directed distances

$$h(A, B) = \frac{1}{n_A} \sum_{a \in A} B_D(a) \tag{1.5.7}$$

Here n_A is the number of edge pixels in set A. We can see that MHD is still sensitive to outliers as the summation of the distances is affected by the outliers due to occlusion. Another robust version proposed by the authors in [2] is called Least Trimmed Square Hausdorff Distance (LTS-HD), given by

$$h_{LTS}(A, B) = \frac{1}{K} \sum_{i=1}^{K} B_D(a)_{sorted}(i) \tag{1.5.8}$$

where K and $B_D(a)$ are as defined in PHD and $B_D(a)_{sorted}$ is the sorted $B_D(a)$ in ascending order. The measures described above make it robust against the *constant* type of partial occlusion because the pixels corresponding to that portion will give us high dissimilarity values from the DT.

1.6 NCC and HD

We have seen in previous section that the directed distances in HD are tuned to deal with the occlusion. The directed distance give dissimilarity of one set to the other set. As we are accustomed to use edge images with HD, we have two directed distances i.e., h(A,B) and h(B,A). If we want to use pixel intensities instead of edges to show dissimilarity between two sets, we shall have one directed distance between A and B. The directed distance can be based on max value of all the pixel distances (HD), or a ranked pixel distance (PHD) or an average of the all pixel distances (MHD) or an trimmed average (LTS-PHD). We shall introduce a novel form of calculating this directed distance in the next chapter.

1.7 Organization of the thesis

The rest of the thesis is organized as follows: Chapter 2 gives an overview of the literature about image registration under partial occlusions. Chapter 3 details the proposed solution. Chapter 4 provides simulations of the proposed algorithm. The detailed comments are also provided about the outcomes of the simulations. Finally Chapter 5 concludes the work and give some future research directions.

Chapter 2

LITERATURE SURVEY

This chapter surveys different image registration algorithms based on NCC which deal with partial occlusion.

2.1 Patch based approaches

Detecting the template when it is partially occluded in the reference image, there are patch based approaches. At every candidate (u, v) location, the template and the reference image under template is divided into a number of overlapping/non-overlapping patches. Each small patch of template image is independently matched with the corresponding patch of the reference image using NCC. The resulting NCC values are added up to give the similarity measure at that (u, v) location [5]. The motivation to use patches is that, if there is an affine (linear) transformation between the local patch of the test and the template image, the local patch will give high value of NCC. This keeps the NCC surface peaked in spite of the local occlusion. Even if the local patch(es) is (are) occluded the remaining patches of the template play main role in matching without being influenced by the occluded pixels. Figure (2.1) shows a template divided into non-overlapping patches [1]. The absolute of the resulting NCC values are added up to give the similarity measure at a location [6]. This algorithm handles even lo-

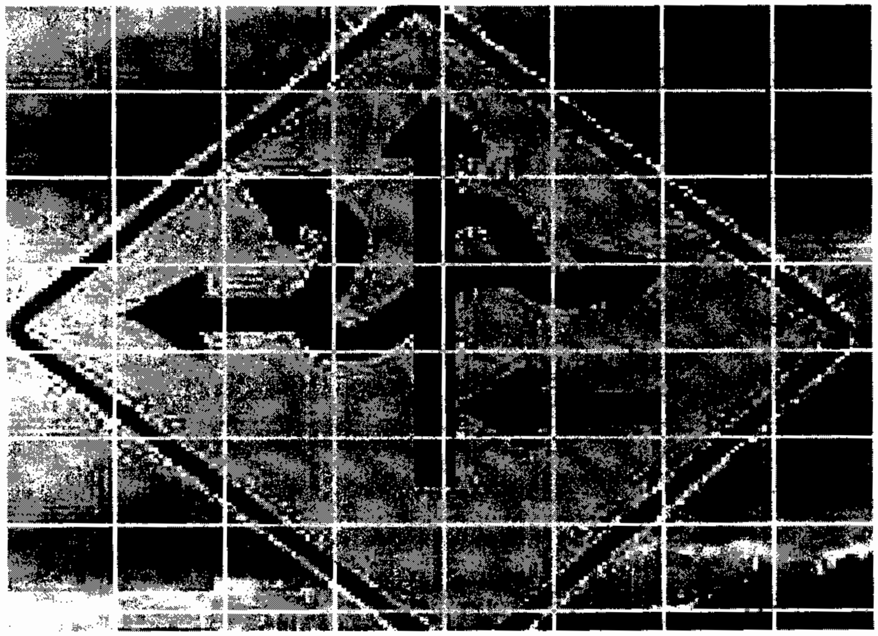

Figure 2.1. A template divided into non-overlapping patches [1]

cal intensity reversals and is useful when matching images taken with different sensors.

The local variation/occlusion may not coincide with the non-overlapping patches. Some work using particle filtering is done in [5] to decide the size and distribution of patches within the whole template. If we opt to use overlapping patches, the complexity increases, even further.

Another limitation of the method is that it requires coherent occlusion and cannot handle random pixel corruption scattered all over the template. It should be noted that the randomly located corrupted pixels are equally bad for global template matching as are the coherent corrupted pixels.

2.2 Pixels based approaches

The authors in [7] detect occluded pixels using the EM algorithm. They then use weighted NCC. The weighted NCC is given by

$$NCC_w(u,v) = \frac{\sum w(f-\overline{f})(t-\overline{t})}{\sqrt{\sum w(f-\overline{f})^2 \sum w(t-\overline{t})^2}} \tag{2.2.1}$$

The contribution from each pixel is weighted to calculate the weighted NCC. The problem with these algorithms is that explicit algorithms are required to detect the occluded pixels so that they can be down weighted.

2.2.1 Increment Sign Correlation coefficient (ISC)

In Increment Sign Correlation coefficient (ISC) algorithm [8], the reference image f and template t are independently converted to binary codes b_i^f and b_i^t, respectively, based on intensity incremental values. The binary codes for the reference image $[b_1^f, b_2^f, ..., b_{n-1}^f]$ are defined as

$$b_i^f = \begin{cases} 1, & if f_{i+1} \geq f_i \\ 0, & otherwise \end{cases} \tag{2.2.2}$$

The same applies to the binary codes for the template image. The ISC is given by the XNOR of these binary codes as shown below

$$NCC_{isc}(u,v) = \frac{1}{n} \sum b_i^f b_i^t + (1-b_i^f)(1-b_i^t) \tag{2.2.3}$$

2.2.2 Selective Correlation Coefficient (SCC)

The same authors also propose a masked NCC where a mask is decided based on distribution of the binary codes [9], defined above. The method is called Selective Correlation Coefficient (SSC). For all even numbered codes, if the codes are same on the template and the reference, the corresponding pixel value in the mask is set to one otherwise to zero. The odd numbered pixels are given mask value equal to that of the neighboring even numbered pixel. Only pixels with mask value of 1 are used to calculate NCC

ISC keeps partial occlusion effect limited to local binary codes. SCC builds on ISC and masks out bad pixels from taking part in the NCC calculations. Both seem to work well for spatially coherent occlusion. There is a risk that SCC in case of randomly located corrupted pixels will fail because so many pixels will be masked out to be included in the NCC calculations.

2.3 NCC variant

NCC is also given by [10]

$$NCC_{ssd}(u, v) = 1 - 0.5 \sum (f' - t')^2 \tag{2.3.1}$$

The f' and t' are zero-mean unit normalized vectors of the reference image and the template, respectively [10]. We call this NCC_{ssd} because the term on the right hand side represents sum of squared differences between f' and t'. We will come back to this definition of NCC in the next chapter again.

Chapter 3

PROPOSED SOLUTION: ROBUST NORMALIZED CROSS CORRELATION (RNCC)

As noted in the previous chapter, NCC is given by [10]

$$NCC_{ssd}(u,v) = 1 - 0.5\sum(f' - t')^2 \tag{3.0.1}$$

The f' and t' are zero-mean unit normalized vectors of the reference image and the template, respectively. We call this NCC_{ssd} because the term on the right hand side represents sum of squared differences between f' and t'. This form also suffers from the same problems of partial occlusion.

3.1 Robust NCC (RNCC) like Robust Hausdorff

The squared differences in Equation (3.0.1) give dissimilarity for the corresponding pixels as we had pixel distances in the directed Hausdorff distance formulas. This is similar to the pixel distances/disimilarities in the directed Hausdorff distance formulas. We notice that the pixels that contribute negatively to NCC are represented by the large squared difference values. We, therefore, suggest not to include the large squared differences in the summation. Our algorithm is given below

$$NCC_{rncc}(u,v) = 1 - 0.5\sum_{i=1}^{K}(f^{'} - t^{'})^2_{sorted} \qquad (3.1.1)$$

K gives the fraction of total number of pixels being matched. For example if want to match only best 75% of the template points , we shall set $K = 0.75 * n_t$, where n_t is the number of pixels in the template. This will make the global correlation robust to all types of partial occlusions mentioned above. Our algorithm is similar in nature to LTS-HD given in Equation (1.5.8).

The number of pixels not included should be linked with the template size and will represent the expected occlusion or local intensity variations. Finally we convert the summation representing dissimilarity into NCC which gives similarity. Note that the pixels corresponding to the large squared differences may or may not be contagious.

We normalize the two images independently, which bears resemblance with ISC method. We detect the pixels to be discarded/masked once we have squared difference between them. This bears resemblance with SSC method.

One variation of RNCC is, we identify the pixels as above and run a separate correlation for the non-occluded pixels. We shall refer to this method as $RNCC_2$ in our simulations. We have seen (please refer to the simulations in next chapter) that the difference of correlation values of the two methods is very small. Our approach is novel in the sense that it avoids an explicit procedure to detect occluded pixels.

As far as computational complexity is concerned, the term f' can be efficiently calculated using integral images [3]. Some applications may suit f' calculations offline. The term t' only needs to be calculated once.

Our approach is different from patch based approach as it does not require a full correlation estimation at patch level to determine the local occlusions. Local occlusions are available as a by product of correlation of the full template itself.

The proposed approach is applicable wherever NCC is used i.e, object detection, biometric (forensics), tracking, stereo (give few references) etc.

we are taking the sense of Hausdorff in dropping some dissimilarity from higher end to tackle partial occlusion. Like Hausdorff, our algorithm does not assume any fixed location for occlusion.

Chapter 4

SIMULATIONS

We shall simulate different types of occlusions and discuss the results. We exclude the patch based approaches from the comparison because their computational complexity is too high to be considered for real time systems.

4.1 Partial occlusion of template by Gaussian Noise

The rice image was corrupted by Gaussian noise of variance 25 in Figure (4.1) in a spatially coherent portion. The noise was contained to 15% contagious pixels. We dropped squared differences of top 10% pixels for RNCC. We see that this value should be proportional to the variance of the Gaussian noise. Higher the variance, higher will be the degradation in the NCC value. We demonstrate that the otherwise NCC of one has reduced to 0.8332. The comparison of different algorithms is given in Table (4.1) Figure (4.2) shows the scatter diagram of the pixels of

Table 4.1. Comparison of different NCC values: Partial Gaussian occlusion

NCC	RNCC	RNCC2	ISC	SCC
0.8332	0.9865	0.9924	0.9271	0.8986

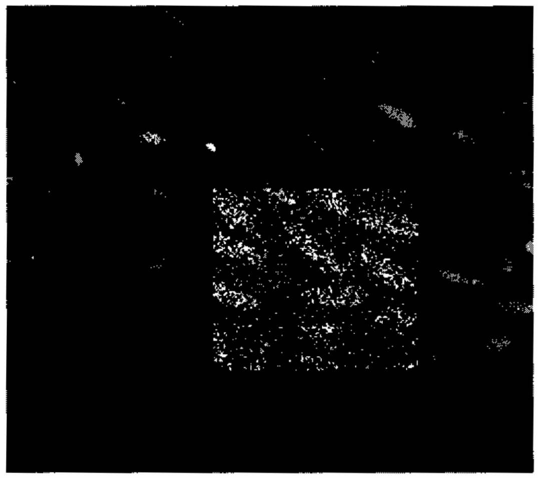

Figure 4.1. Rice image partially corrupted by Gaussian noise

rice and its corrupted image pixel intensities. The pixels not on the straight line with a positive slope cause degradation of the global NCC from one to 0.8332. Green pixels are the corrupted pixels detected by our algorithm. Note that we were successful in detecting majority of the corrupted pixels. The only parameter to be tuned in our algorithm is how many of pixels we are going to throw. This can be learnt by looking at the data of a particular application. There is a very slight difference between $RNCC$ and $RNCC_2$. Our proposed algorithms outperform the ISC and SCC algorithms values as shown in Table (4.1).

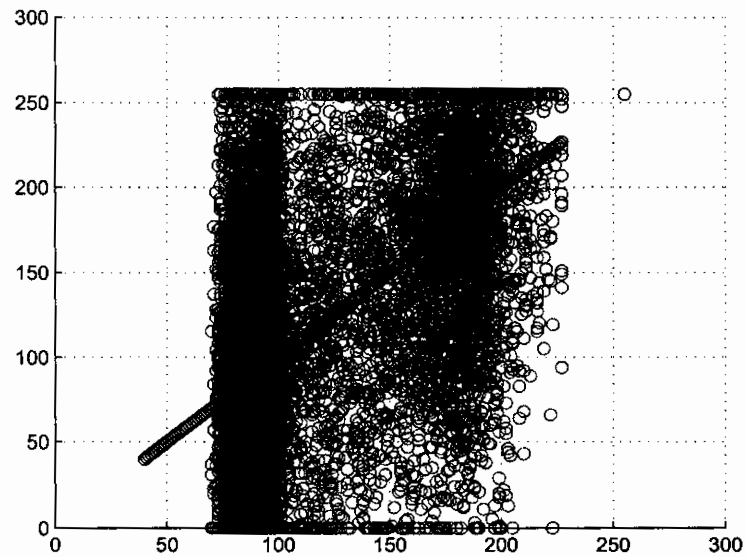

Figure 4.2. Scatter diagram between Rice image and its image corrupted partially by Gaussian noise

4.2 Full template corrupted by salt & pepper noise

5% of the the rice image pixels were corrupted by salt & pepper noise in Figure (4.3). We dropped squared differences of top 5% pixels for RNCC. Note that we are assuming that our template (the full rice image) or its location in some larger scene has been corrupted by salt & pepper noise. We demonstrate that the otherwise NCC of one has reduced to 0.7956. Note that only 5% of pixels corrupted reduced the correlation by more than 20%. The comparison of different algorithms is given in Table (4.2) Figure (4.4) shows the scatter diagram of the

Table 4.2. Comparison of different NCC values: 5% pixels in Salt & pepper occlusion

NCC	RNCC	RNCC2	ISC	SCC
0.7956	0.9879	0.9999	0.9527	0.8858

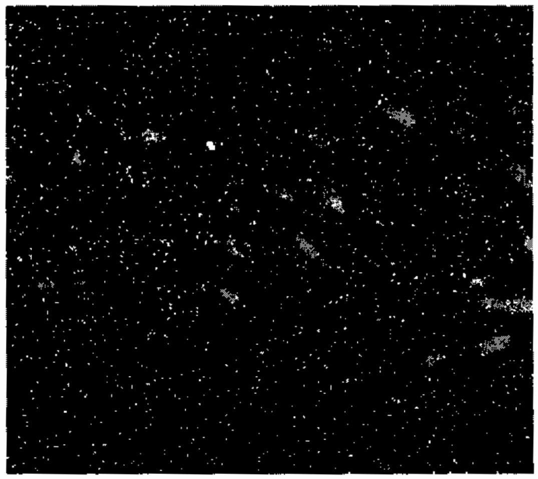

Figure 4.3. Rice image corrupted by salt & pepper noise

pixels of rice and its corrupted image pixel intensities. The pixels not on the straight line with a positive slope cause degradation of the global NCC from one to 0.7956. Green pixels are the corrupted pixels detected by our algorithm. Note that we were successful in detecting majority of the corrupted pixels. The only parameter to be tuned in our algorithm is how many of pixels we are going to throw. This can be learnt by looking at the data of a particular application. Finally there is a very slight difference between $RNCC$ and $RNCC_2$ values. Our proposed algorithms outperform the ISC and SCC algorithms values as shown in Table (4.2).

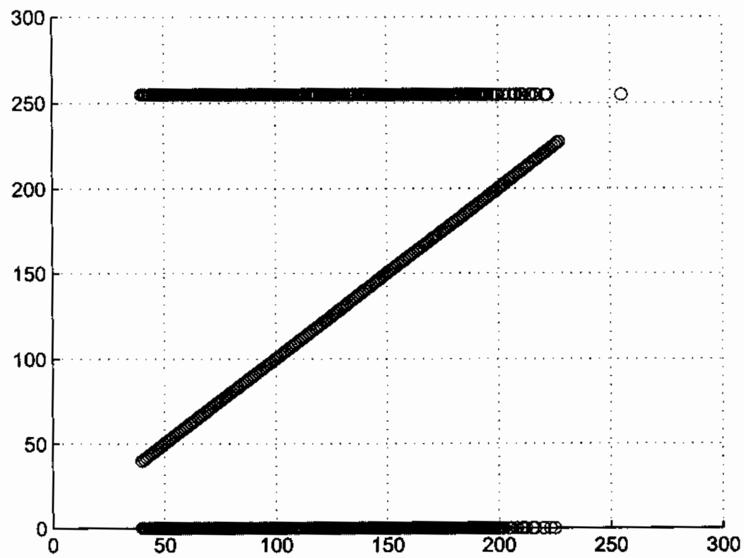

Figure 4.4. Scatter diagram between Rice image and its image corrupted by salt & pepper noise

4.3 Partial occlusion of template by a constant value

The rice image was corrupted by lowering 15% of contagious pixel values to a constant value. in Figure (4.5). We dropped squared differences of top 7% pixels for RNCC. We demonstrate that the otherwise NCC of one has reduced to 0.5647. The comparison of different algorithms is given in Table (4.3) Figure (4.6) shows the scatter diagram of the

Table 4.3. Comparison of different NCC values: A constant low value occlusion

NCC	RNCC	RNCC2	ISC	SCC
0.5647	0.8667	0.8661	0.9460	0.6925

Figure 4.5. Rice image corrupted by a constant low value

pixels of rice and its corrupted image pixel intensities. The pixels not on the straight line with a slope cause degradation of the global NCC from one to 0.5647. Green pixels are the corrupted pixels detected by our algorithm. Note that we were successful in detecting majority of the corrupted pixels. The only parameter to be tuned in our algorithm is how many of pixels we are going to throw. This can be learnt by looking at the data of a particular application. Finally there is a slight difference between $RNCC$ and $RNCC_2$. ISC outperforms our proposed algorithms as shown in Table (4.3). This is possible a constant down occlusion renders binary codes to be zero. This mistakenly gives a high value of XNOR because the original rice image also has zero binary codes at the corresponding locations. The SCC (which builds on ISC codes) is inferior to our algorithms. This again proves supremacy of our algorithms as SCC could not mask out pixels under the occlusion and resultantly had a lower correlation value.

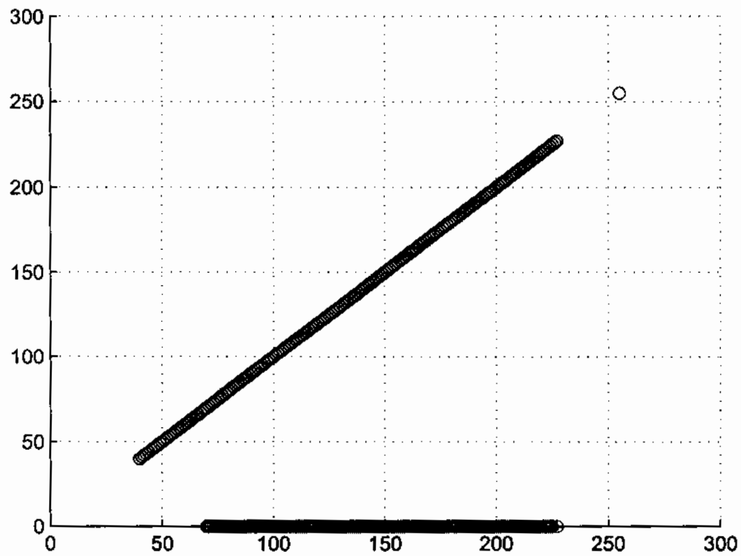

Figure 4.6. Scatter diagram between Rice image and its image corrupted partially by a constant low value

4.4 Partial occlusion of template by intensity reversal

The rice image was corrupted by subjecting 15% of contagious pixel to a intensity reversal. in Figure (4.7). We dropped squared differences of top 15% pixels for RNCC. We demonstrate that the otherwise NCC of one has reduced to 0.6877. The comparison of different algorithms is given in Table (4.4) Figure 4.8) shows the scatter diagram of the pixels

Table 4.4. Comparison of different NCC values: Partial intensity reversal

NCC	RNCC	RNCC2	ISC	SCC
0.6877	0.9985	1	0.8940	0.9021

Figure 4.7. Rice image corrupted by partial intensity reversal

of rice and its corrupted image pixel intensities. The pixels not on the straight line with a positive slope cause degradation of the global NCC from one to 0.6877. Green pixels are the corrupted pixels detected by our algorithm. Note that we were successful in detecting majority of the corrupted pixels. The only parameter to be tuned in our algorithm is how many of pixels we are going to throw. This can be learnt by looking at the data of a particular application. Finally there is a slight difference between $RNCC$ and $RNCC_2$. Our proposed algorithms outperform the ISC and SCC algorithms values as shown in Table (4.4).

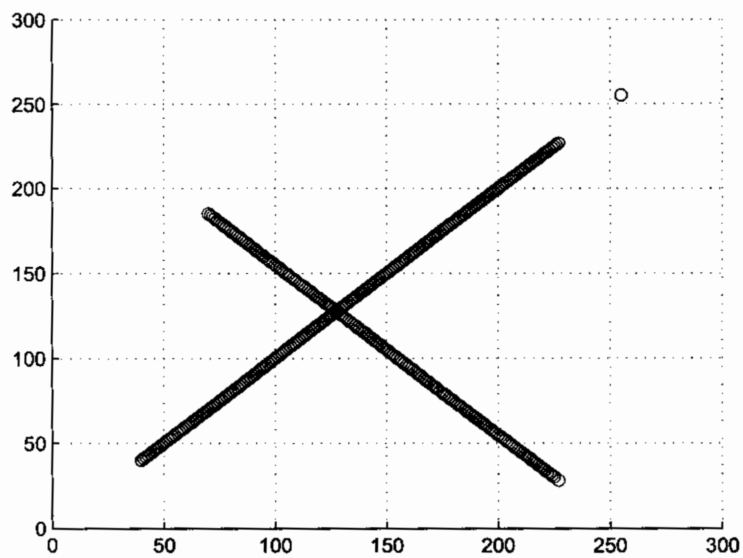

Figure 4.8. Scatter diagram between Rice image and its image corrupted partially by intensity reversal

Chapter 5

CONCLUSIONS AND FURTHER RESEARCH

In this chapter general conclusions are drawn and suggestions for further research are given.

We have proposed a novel and robust algorithm to perform image registration for object/target recognition under partial occlusion. The robustness to occlusion takes its intuition from the robust LTS-HD algorithm. This was possible by using a particular form of the Normalized Cross Correlation (NCC).

The corrupted pixels are detected as a by product of the NCC calculations keeping the computational complexity of our algorithm low.

The algorithm is able to handle partial occlusion whether it is in the form of randomly located corrupted pixels (noise) or as a contagious block of corrupted pixels.

Even if coherent occlusion is present, location of the occluded pixels is not fixed so the algorithm handles occlusion in any part of the target and matches based on the given percentage of the best pixels.

We are taking the sense of LTS-HD Hausdorff in dropping some dissimilarity from higher end to tackle partial occlusion.

Like Hausdorff based algorithms, our algorithm does not assume any fixed location for occlusion.

$RNCC_2$ bears resemblance with SCC algorithm as both first mask out occluded pixels and then estimate NCC over the reminding pixels.

Adaptive version of our algorithm where the elimination of large squared difference values is made intuitive will be an interesting future research direction.

BIBLIOGRAPHY

[1] G. Guo and C. R. Dyer, "Patch-based image correlation with rapid filtering," in *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2007.

[2] M. P. Dubuisson and A. K. Jain, "A modified Hausdorff distance for object matching," in *2th Int. Conf. on Pattern recognition*, pp. 566–568, 1994.

[3] J. P. Lewis, "Fast normalized cross-correlation," *Vision Interface*, pp. 120–123, 1995.

[4] D. P. Huttenlocher, G. A. Klanderman, and W. J. Rucklidge, "Comparing images using the Hausdorff distance," *IEEE Trans. PAMI*, vol. 15, pp. 850–863, 1993.

[5] A. Nakhmani and A. Tannenbaum, "Particle Filtering with Region-based Matching for Tracking of Partially Occluded and Scaled Targets," *SIAM J. Imaging Sciences*, 2010.

[6] A. Baig, M. A. Chaudhry, and A. Mahmood, "Local Normalized Cross Correlation for Geo-registration," in *IBCAST*, 2012.

[7] J. Pilet, V. Lepetit, and P. Fua, "Retexturing in the Presence of Complex Illumination and Occlusions," in *ISMAR*, 2007.

[8] K. S. Murase and I. S. Igarashi, "Robust image registration by increment sign correlation," *Pattern Recognition*, vol. 35, no. 10, pp. 2223–2234, 2002.

[9] K. S. Murase and I. S. Igarashi, "Using selective correlation coefficient for robust image registration," *Pattern Recognition*, vol. 36, no. 5, pp. 1165–1173, 2003.

[10] J. L. Rodgers and W. A. Nicewander, "Thirteen Ways to Look at the Correlation Coefficient," *The American Statistician*, vol. 42, no. 1, pp. 59–66, 1988.