Image Quality Analysis of Segmented Iris using Filters

Sunil Kumar, Vijay Kumar Lamba, Surender Jangra

Abstract: Quality of an Image has a significant impact on the overall performance of an image processing system. In this technical era, when everything is being digitized, many of us prefer to transfer data in a digital form; to be more secure while using digital devices through biometric sensors. We encounter many more such instances in our day to day life where these devices and sensors are deployed. The biometric devices or systems require a quality input to achieve quality performance. There is always a need to enhance the quality of the sample after its acquisition. In this paper, we are going to discuss image quality enhancement for biometric recognition system where iris samples have been used; by proposing an image quality analysis approach of segmented irises based on quality filters. It means input images are not directly passed to the filters, they are firstly segmented and then segmented parts will be enhanced using different filters. Segmentation is one of the initial key steps of recognition systems and has a significant role in the biometric systems as the performance results of the system's subsequent stages depend upon the segmentation results. We have segmented iris images into three major parts namely ROI, pupil and sclera. ROI represents the region of interest i.e. iris. Moreover, iris images from four directions viz. up, straight, left and right are taken into consideration to achieve more promising results. Unlike general case, filters are applied for enhancement after segmenting the input images. To measure the quality of input samples, various image quality metrics have been calculated and analyzed comprehensively to reach to the conclusion that Gaussian filter performs better as compared to Average and Circular Average Filter.

Index Terms**: *Biometric, Iris, Image Quality Analysis, Segmentation, Filters.***

I. INTRODUCTION

With rapid pace technological advancements, everything is being digital these days. So, there is an alarmingly growing requirement of automated systems which can provide better services. These systems are based on recent technological advancements in the fields of Image Processing, Computer Vision, Machine Learning, Artificial Intelligence, Robotics, Natural Language Processing and many more [1]. Because of this digitization, security becomes a primary concern for such systems. Now-a-days, biometric based security systems are very popular and are being used in boarder access control, banking services, high-security institutions like nuclear facilities, military bases etc. for protecting sensitive data and online tracking of system operations.The security systems based on biometrics are very fast and easy to use. Moreover, there is no need to memorize a biometric trait as opposed to a PIN or password [4]. Biometrics is based on physiological or behavioral characteristics of a person which cannot be lost and forgotten. In recent times, Biometrics has helped to reduce the amount of fraud cases. Biometrics traits like finger-print face and iris are mainly used as compared to other traits as they are widely researched and implemented and acceptable throughout the wide range of applications worldwide [11].In this work, we have used iris as biometric trait because iris recognition systems have been widely adopted by many countries for the identification of the people. Examples are India's UIDAI program, USA's Homeland and Boarder Security, UAE's Airport Access Control etc. [3]. Iris being the inner visible part of the eye is hard to forge and duplicate and very convenient to use since it has low false acceptance and false rejection rates. The numbers of other advantages of using irises for authentication are: scalability, stability, speed, non-intrusiveness, non-invasiveness, randomness, uniqueness and reliability. Generally, Iris Recognition System contains five steps (i) Acquisition (ii) Pre-Processing (iii) Segmentation (iv) Normalization and Feature Extraction and (v) Matching. The real success of iris recognition system depends upon the quality of iris image as well as segmentation. So, both of these are worth attention. In an iris based recognition system, pre-processing is an essential step to enhance the quality of the sample data and various methods have been used for the same depending upon the requirements. Generally, sample input image quality is enhanced first and then supplied to the next steps of the system. This will indirectly get the performance of the biometrics system better [15]. The quality enhancement may be done both before and after the segmentation. Unlike usual cases, we have opted to perform enhancement after segmenting the iris input sample. Also, the selection of enhancement method is very crucial because it can even degrade the performance of the system if enhanced images are not of good quality. So, the main objective of this paper is to enhance the quality of the input samples so that higher recognition rates can be achieved in future. For this, we have proposed segmentation based quality enhancement technique in which iris sample is segmented into three vital portions followed by the application of three different filters Gaussian, Average and Circular Average are applied. As a follow-up process, the performance of each filter on each segmented portion on the basis of various quality parameters is analyzed.

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The following sections include the detailed description of the proposed work and exiting algorithms. Section 2 describe the various existed quality enhancement mechanisms where as section 3 describes proposed work in which segmentation mechanism, and used filter banks are described and results of this proposed mechanism are analyzed using various samples and compared on the basis of different parameters given in section 4 followed by conclusion presented in Section 5.

II. QUALITY ENHANCEMENT IN IRIS RECOGNITION

Iris recognition based systems are one of the systems which are still in their developing stages. There are so many existed recognition systems but still these systems need improvement. For this various researches has been done on the same [28-30]. In biometric systems, the quality of the samples is directly affecting the performance of the systems. So the pre-processing step also needs more attention. In the pre-processing step, the quality of the samples will be improved because this step reduces the noise present in the samples from external interferences while they acquire from sensors. Various research works have been dedicated to the enhancement of iris quality before actually using it for verification or authentication purposes.

Table 1: Existed Image Enhancement Techniques

Ref.	Authors	Enhancement Method/Filter
[5]	Sabarigiri and Karthikeyan	Gabor Filters
[6]	Sanpachai and Malisuwan	Histogram Equalization
[7]	Feddaoui et al.	Gabor filter along with Gaussian filters
[8]	Vatsa et al.	SVM based Technique
[9]	Monro et al.	Background Subtraction
[10]	Poursaberi and Araabi	Wiener 2D Filter
[12-13]	Ma et al.	Background Subtraction
[25]	Hajari et al.	Camera reflection pixel Identification and Removal
[31]	Sun et al.	Contour based method and histogram Equalization
[32]	Sazonova and Schuckers	Masking followed by LIP enhancement and stretching
[33]	Yan et al.	Improved ACE algorithm
[34]	Tammam and Khalil	Complex matched filter and masking
[35]	Ismail et al.	Contrast Limited Adaptive Histogram Equalization
[36]	Xu et al.	Background illumination and subtraction, bicubic interpolation and wiener Filter

III. PROPOSED WORK

The main focus of this work is to develop a mechanism to improve the quality of the sample so that the performance of the recognition system will be improved. For this, the new proposed quality enhancement method is divided into two phases: (i) Segmentation and (ii) Filtering and testing of different filter-banks is done as shown in fig 2. Generally segmentation is performed after pre-processing but here segmentation works like decomposition of the sample and it divides iris image into three main components and that are: (a) Iris (ROI), (b) Pupil, and (c) Sclera. Each part is then separately passed to the filter-banks and its performance is calculated on the basis of different parameters.

A. Sample Acquisition

In this work, dataset of multi-angled eyeballs has been used. This dataset contains samples from 100 subjects for left, right; up and straight direction angles. So, in total, we had 400 images. We used MATLAB simulator for the simulation of the proposed quality enhancement method. After acquisition, samples were passed to the segmentation phase.

B. Segmentation of iris

To enhance the image quality of the input sample, unlike general practice, we have segmented the iris (ROI), sclera and pupil from the input images before actually applying any filters. This will indirectly increase the quality of image taken for the recognition purpose. In this section, the details of segmentation process are discussed.

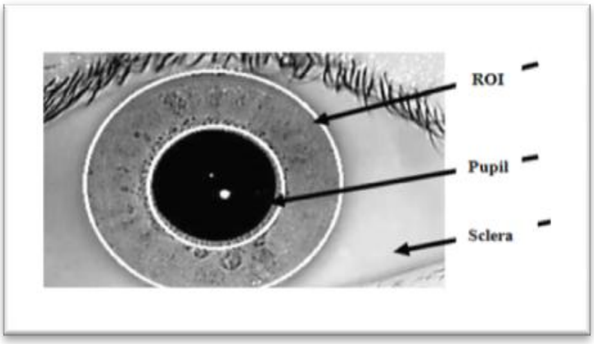


Fig 1: Parts of Iris

Then as according to radius the region of the circular pixels are selected and lines are drawn on the same region and find the outer circle region and inner circle region. From the center, this algorithm starts detecting circular pixels and inner circle is drawn where the intensity of the pixels are changed from the center and same in case of outer circle. Because the outer region of the pupil having different intensity pixels and similarly iris and sclera has different intensity pixel, this will help to detect outer and inner circle in this algorithm

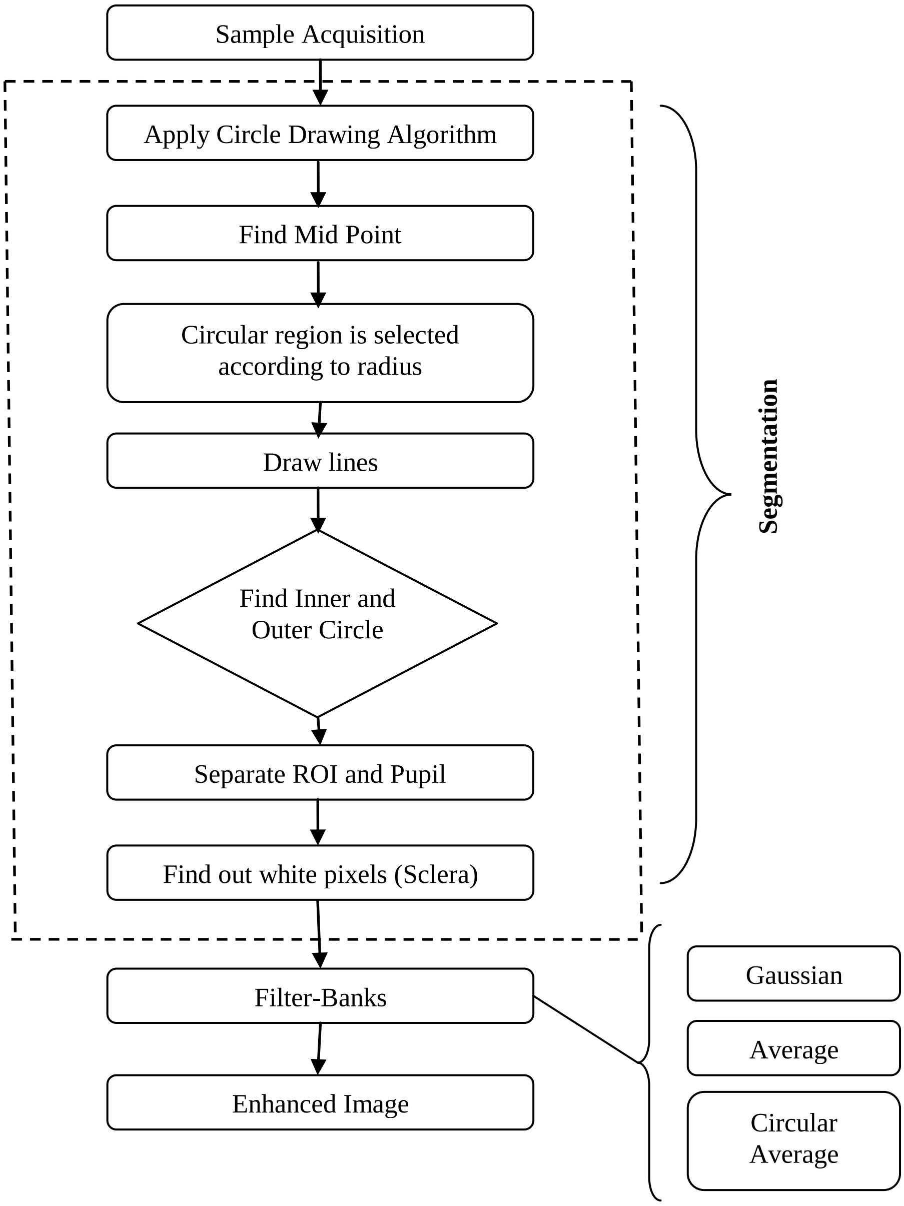


Fig 2: Flow of proposed work

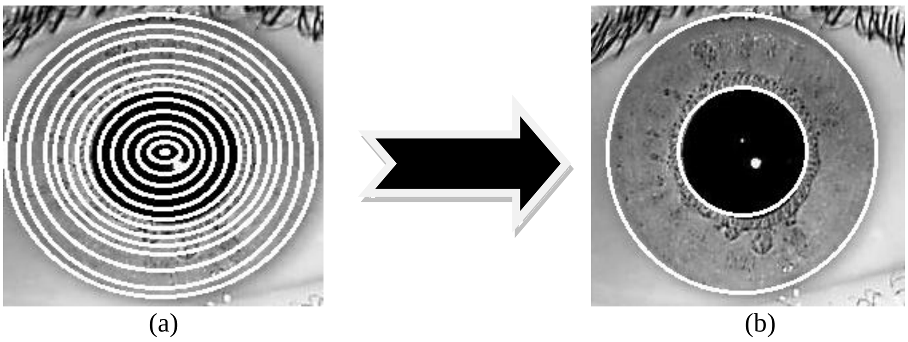
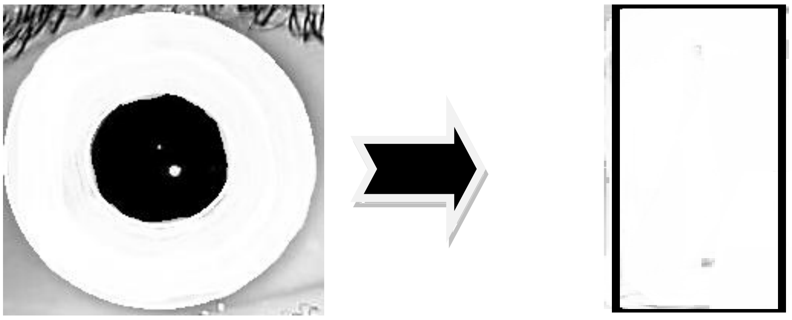


Fig 3: (a) Circle Drawing, (b) Inner Circle and Outer Circle

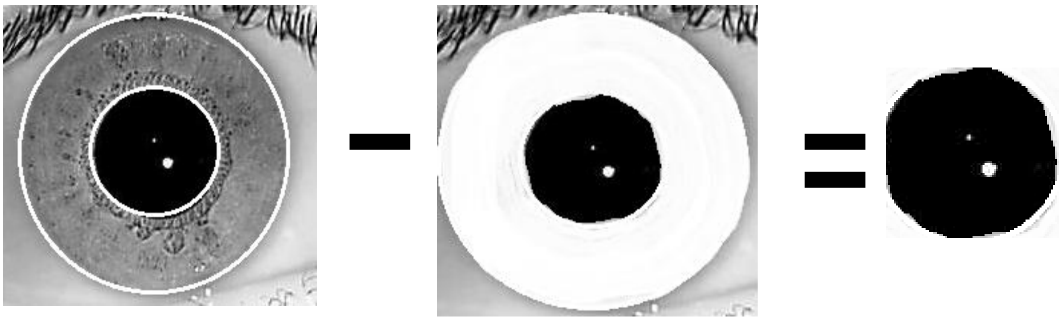
Region of Interest (ROI): ROI is specifically that area where user's interest is more. In our case, Iris area is the most important one. It is the annular part between pupil boundary and iris boundary i.e. inner and outer circles respectively. In this work, these pixel values are detected and stored in an array. For this, we have used filling algorithm in which inner circle boundary pixels are selected first and then filling algorithm select the pixels by using eight connected regions up to outer circle boundaries and form an array of pixels as shown in fig. 3 and fig. 4.



(a) (b)

Fig 4: (a) ROI area, (b) ROI in single array

Pupil: The pupil is a gap situated in the focal point of the iris of the eye that enables light to strike the retina. It seems dark since light entering the pupil is either consumed by the tissues inside the eye specifically, or assimilated after diffuse reflections inside the eye that mostly miss exiting the narrow pupil. In this work, to extract pupil from the full eye image, we subtracted the extracted ROI region from the original image as shown in fig.5 and these pixels are further stored in the array.



(a) (b) (c)

Fig 5: (a) Iris, (b) ROI, (c) Pupil

Sclera: It is the white portion of the eye, elliptical in shape, which is the outer region of the eyeball. It is the fibrous, protective, opaque, and outer layer of the human eye which contains some elastic fiber and aqueous material called collagen. For this, we converted iris image into black and white image means logical image and extract the white pixels of the image and stored them into an array.

C. Filter-banks for Quality Enhancement

To enhance the quality of an image is one of the key steps in the field of image processing and biometric systems. There are so many filters available to enhance the quality of the image. In this work, we segmented the iris image into three parts and then apply filters on each segmented area. This will improve the image quality better rather than we apply it on the whole image. For this work, three filters have been used to enhance the quality of sclera, pupil and ROI individually. The application of these filters will result an enhanced iris image which can further be processed to deliver the better results for recognition. These filters are:

(a) **Gaussian Filter**

Gaussian Filter is a filter that is used to remove the noise and extra details of an image and to make it smooth. It is nearly same as mean filter but it is of bell shaped [18]. In this work, we have used 2D-Gaussian Filter which is given as:

$$G(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad \text{(i)}$$

(b) **Average Filter**

Average Filter is also smoothes the image. It is a windowed filter of linear class and works as low pass filters [16]. The basic idea is that this filter takes the average of the neighbourhood.

$$G(x,y)=\frac{1}{n}\sum_{i=1}^{n}x_i y_i \qquad \text{(ii)}$$

(c) **Circular Average Filter**

It takes the average of all elements in a window around each location. Let us say we are looking at a pixel with coordinates (100, 200) and had a disc of radius 10. So it would take all pixels in a circle from 90 to 110 and 190 to 210, multiply them by the values in the fspecial array, which are 1's in the disc, and 0's on the corners which are not included in the disc, then sum them up, and set the output value at (100, 200) to that sum. This will give the effect of blurring the image [14]. Each of this filterbank is applied on the segmented data samples and then analysis is done on the basis of different image quality parameters.

When filters are applied on the segmented portions (sclera, pupil and ROI) then this will help to remove noise from both inner and outer portions of the iris image and the quality of image is enhanced more as compare to if the filter is applied on the full image without segmentation.

IV. RESULTS ANALYSIS

To analyze the performance of this system, the data set of 100 samples for each Left, Right, Up and Straight eyeball have been used in this work and segment each of the sample into three parts i.e. (i) Pupil (ii) Sclera and (iii) ROI. We have used three filter banks for each segmented part and analyzed their performance on the basis of different quality parameters given in Table 2 below.

Table 2: Parameters and Details

Sr. No.	Parameter Name	Parameter Formula	Remarks
1.	Peak Signal to Noise Ratio (PSNR)	$PSNR = 10\log\frac{255^2}{MSE}$	Higher the PSNR, lesser the noise.
2.	Mean Square Error (MSE)	$MSE = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}[x(m,n)-x'(m,n)]^2$	Lesser the value of MSE, better the performance of the algorithm.
3.	Structure Similarity (SSIM)	$SSIM(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma}$ Where, l is luminance, c is contrast and s is structural correlation	The SSIM index value varies between 0 and 1. The value close to 1 shows the highest correspondence with the original images and vice-versa.
4.	Signal to Noise Ratio (SNR)	$SNR = 10\log\left[\frac{\mathrm{var}(x(m,n))}{mean(x(m,n)-x'(m,n))}\right]$	Signal to Noise ratio, higher the SNR, lesser the noise, better the reconstruction
5.	Average Difference (AD)	$AD = \frac{1}{M*N}\left(x(m,n)-x'(m,n)\right)$	As small as possible, the ideal value is 0.
6.	Structural Content (SC)	$SC = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}x(m,n)^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}x'(m,n)^2}$	It is the ratio of sums of the squares of the original and recovered image pixel values.
7.	Mean Difference (MD)	$MD = \max\left(\lvert x(m,n)-x'(m,n)\rvert\right)$	As small as possible
8.	Laplacian Mean Square Error (LMSE)	$LMSE = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}\left[L\left(x(m,n)-L\left(x'(m,n)\right)\right)\right]^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}\left[L\left(x(m,n)\right)\right]^2}$	As small as possible
9.	Normalized Absolute Error (NAE)	$NAE = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}\left[\lvert x(m,n)-x'(m,n)\rvert\right]^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}\lvert x(m,n)\rvert}$	As small as possible, the ideal value is 0.

We have analyzed performance on 100 samples and parameter wise average performance of the samples for each pupil, sclera and ROI is given in Table 3. Here, result graphs show different image quality metrics / parameters for each segmented part. Also it is shown that results are varied for each segmented part i.e. for instance PSNR of the Pupil for each filter bank is more than that of ROI and Sclera. Therefore, if we enhance each segmented part before actually processing it for recognition, it will affect the performance whether we take it individually or we fuse these parts.

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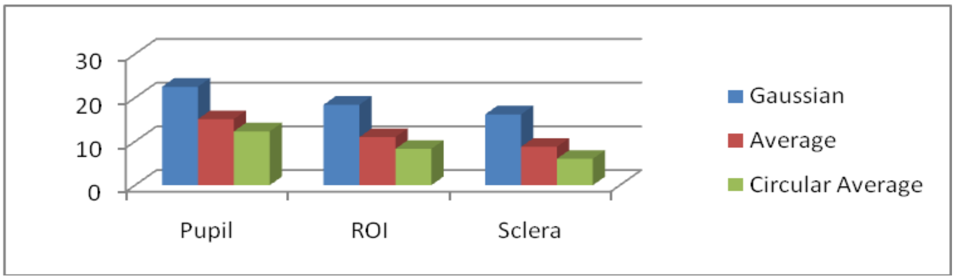
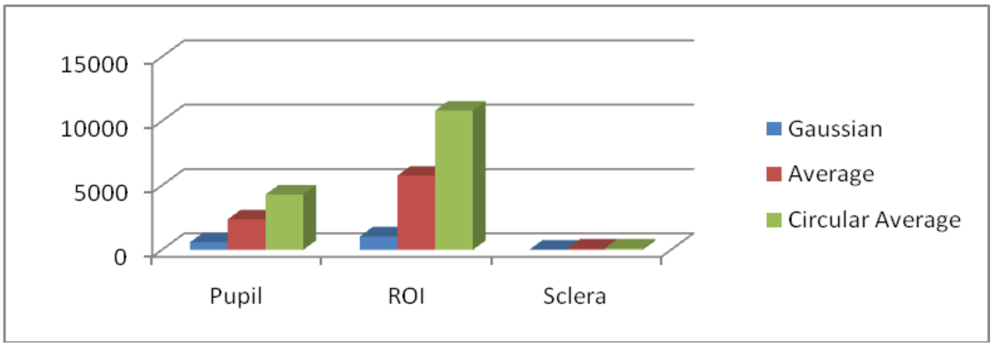
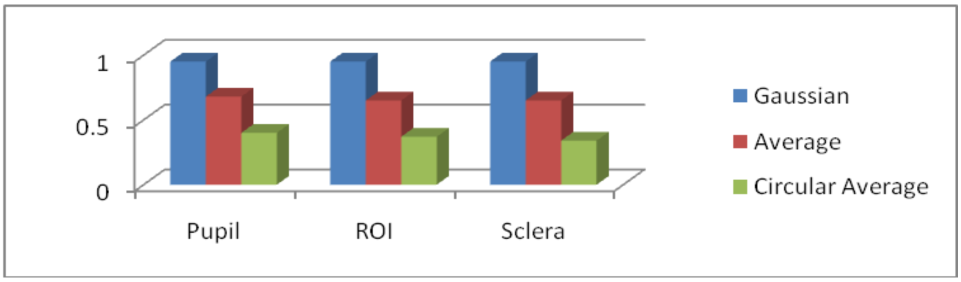
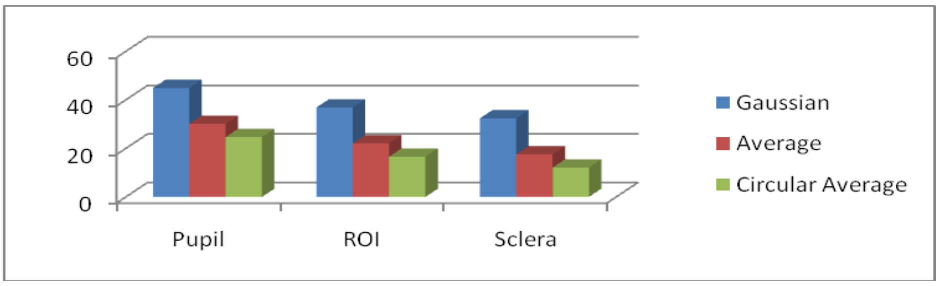
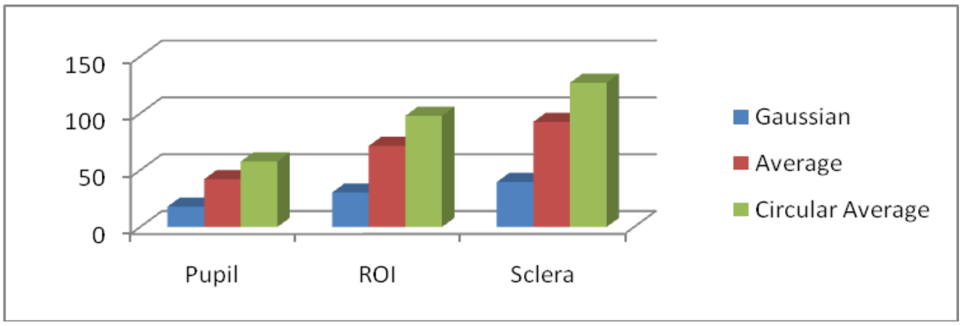
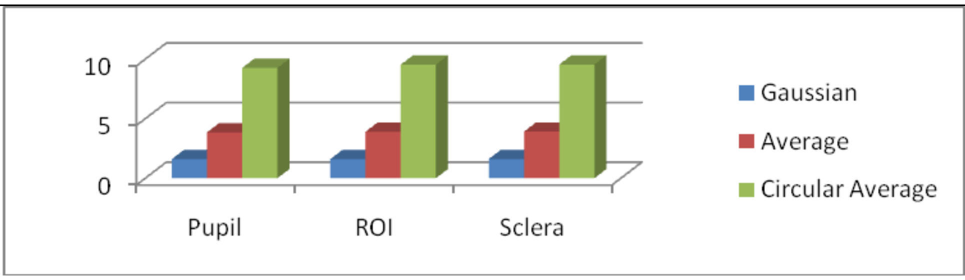
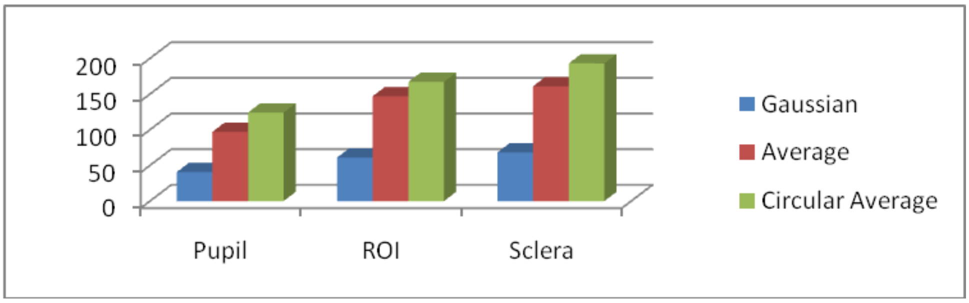
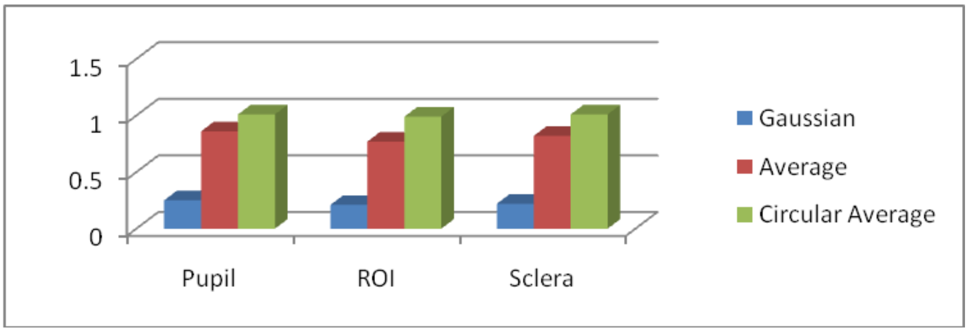
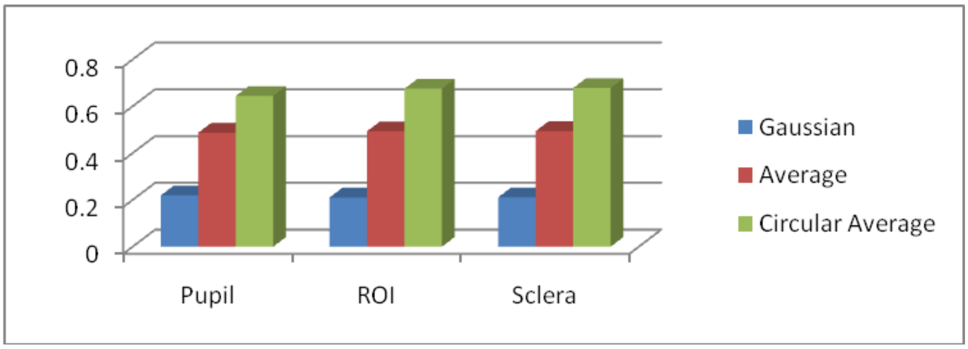
Table 3: Performance for Pupil, Sclera and ROI after Filteration

Parameter	Result Graphs
PSNR	
MSE	
SSIM	
SNR	
AD	

SC	
MD	
LMSE	
NAE	

In this experiment, we used database of Left, Right, Up and Straight Eyeballs and we collected 100 samples for each i.e. we have analyzed the performance of 400 samples in total. The above tables show the average performance of all 400 samples graphically. When we fused the individual results, the average performance of the filters is shown in fig 6. These results shows that on an average PSNR value of Gaussian Filter is better than Average filter by 38% and Circular Average Filter by 53% which shows that Gaussian filter performs better as compare to other filters. Similarly, MSE of the Gaussian Filter is better than Average filter by 79% and Circular Average Filter by 89% which is a great improvement by this filter. SSIM of the Gaussian filter is also more than the other filters and it is better than Average Filter by 30% and by Circular Average by 61% which also shows that Gaussian is better.

Detailed results of this experiment are given in table 4 to table12. Results also show that SNR of the Gaussian Filter is higher than other filters and it shows that the presence of noise is very less in the samples while using Gaussian Filter. The achieved performance of the Gaussian filter is 39% better than Average Filter and 53% better than Circular Average Filter. Similarly, for other parameters, Gaussian filter performs better than Average and Circular Average Filter.

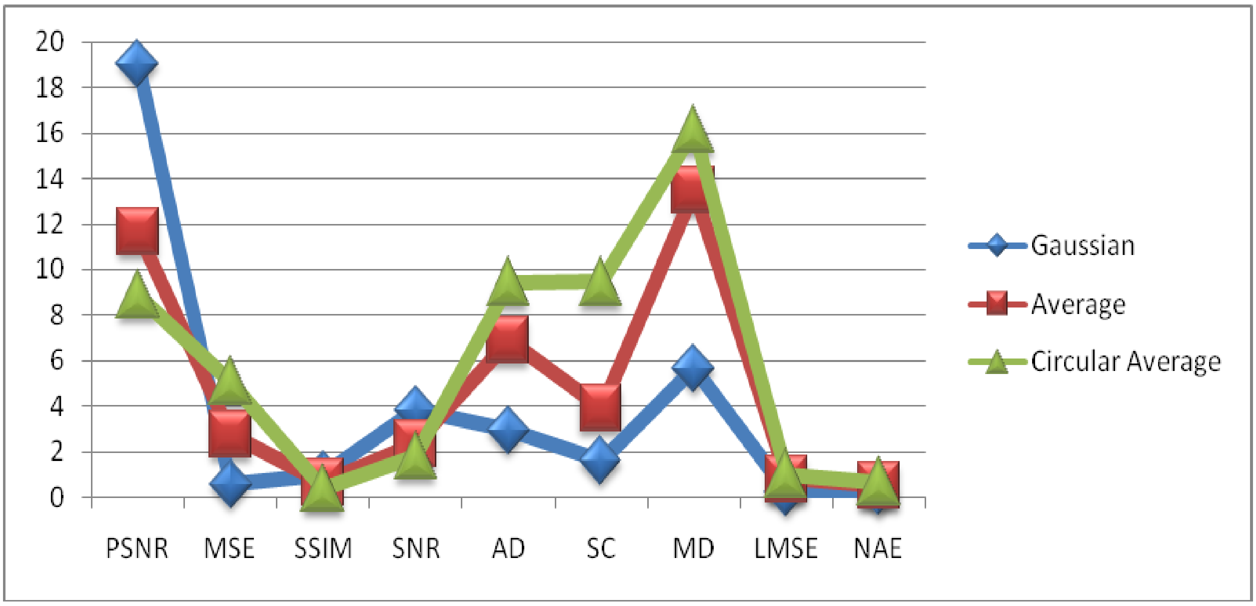


Fig 6: Average Performance of Filer-banks

V. Conclusion

This paper concludes that the quality enhancement is a very crucial factor for biometric security systems as the performance of these systems are merely depends on it. In this work, we first segment Iris Image into pupil, sclera and ROI and then filters were applied on it. We used three different filters Gaussian, average and circular average and calculated its performance by using different performance matrices. After analysis it is clear that segmentation will help to improve the quality of each part and therefore performance of the fused system is improved as compare to if filters applied directly on original image. Results also shows that Gaussian filter achieve better performance as compare to average and circular average filter.

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APPENDIX

Table 4 : PSNR values of 10 values for each Left, Right, Up and Straight Sample (Pupil, Sclera and ROI)

	Sample Number	Pupil				ROI				Sclera			
		Left	Right	Up	Straight	Left	Right	Up	Straight	Left	Right	Up	Straight
Gaussian Filter	1	21.2265	21.1464	20.5144	32.8306	16.9047	17.4024	16.0963	23.0014	16.2646	16.2002	16.2794	18.5456
	2	23.0373	24.1588	23.5744	23.6238	20.5057	19.1006	20.7355	20.9347	15.7713	16.5967	13.5791	16.2605
	3	24.8238	18.9318	23.1935	22.5306	19.0042	15.8337	18.8467	19.565	17.6622	15.1505	16.0261	16.1338
	4	21.7876	22.6193	24.1604	21.3078	17.5497	15.5319	18.2465	15	16.36	15.402	15.8539	15.0061
	5	21.8215	23.8764	18.2013	22.9281	17.6392	22.248	15.7408	20.8378	16.854	16.3176	15.3796	16.4791
	6	18.9677	20.043	21.6993	19.7514	15.2128	19.5749	18.4724	16.4912	15.1436	16.2835	16.4679	16.0587
	7	25.4866	22.6303	22.9264	17.9243	18.6641	20.6826	20.0518	14.954	16.8274	16.1044	16.2664	14.6566
	8	21.498	27.7041	21.3703	25.4325	17.5145	18.4478	15.1453	17.3974	16.2301	16.4369	14.8934	15.5989
	9	20.058	21.2383	23.1498	21.5816	16.4905	16.5152	20.5869	21.6683	16.2079	16.1366	16.6232	18.2045
	10	19.6247	27.6816	21.9049	21.8479	18.8789	21.7865	20.0202	18.556	16.3644	18.149	16.1034	16.2132
Average Filter	1	13.817	13.7434	13.104	25.4565	9.49441	9.99479	8.68598	15.5939	8.86669	8.8017	8.88178	11.1571
	2	15.6284	16.7594	16.1648	16.2043	13.0985	11.691	13.3255	13.528	8.3739	9.19978	6.42871	8.86407
	3	17.412	11.5201	15.7848	15.1163	11.5965	8.42803	11.4375	12.1554	10.2694	7.75227	8.62704	8.73564
	4	14.3865	15.2164	16.7797	13.8943	10.1489	8.12186	10.8381	7.59054	8.96432	8.00281	8.457	7.60687
	5	14.4079	16.4789	10.7956	15.5229	10.2384	14.8429	8.33421	13.4284	9.45966	8.91875	7.982	9.08291
	6	11.5637	12.631	14.2944	12.339	7.80249	12.1687	11.0665	9.08151	7.74505	8.88635	9.07095	8.66007
	7	18.0951	15.2298	15.5084	10.5162	11.2611	13.2754	12.6425	7.5448	9.43124	8.70481	8.8678	7.25852
	8	14.097	20.3031	13.9641	18.0271	10.1092	11.0444	7.73411	9.98885	8.83359	9.03994	7.49395	8.20102
	9	12.6445	13.8189	15.7494	14.1763	9.07993	9.10384	13.1778	14.2639	8.80964	8.73775	9.22641	10.8146
	10	12.2148	20.318	14.498	14.4393	11.4689	14.3783	12.6142	11.146	8.96572	10.759	8.70678	8.8149
Circular Average Filter	1	11.0804	11.0071	10.3715	22.7264	6.76038	7.2627	5.9518	12.861	6.12117	6.05628	6.13587	8.41421
	2	12.8935	14.0299	13.4319	13.4797	10.3653	8.95664	10.5926	10.7968	5.62919	6.45426	3.85454	6.11919
	3	14.6841	8.79003	13.0608	12.3815	8.86368	5.69572	8.70389	9.42183	7.52378	5.00823	5.88177	5.9903
	4	11.6524	12.4805	14.061	11.1721	7.42025	5.38776	8.10484	4.85603	6.21964	5.25839	5.71244	4.86276
	5	11.6738	13.7382	8.06404	12.7854	7.50937	12.1106	5.60195	10.6946	6.71454	6.17294	5.23783	6.33671
	6	8.83726	9.89849	11.5685	9.60429	5.06797	9.43722	8.335	6.34655	5.00086	6.14108	6.32536	5.91441
	7	15.3579	12.4939	12.7828	7.78558	8.53132	10.5421	9.90872	4.81239	6.68506	5.9594	6.12204	4.51421
	8	11.3623	17.5717	11.236	15.2849	7.37832	8.31408	4.99976	7.25599	6.08882	6.29488	4.74974	5.45677
	9	9.90888	11.0847	13.018	11.4398	6.34552	6.36972	10.4441	11.5353	6.06354	5.99186	6.48056	8.06951
	10	9.48527	17.6171	11.7666	11.7067	8.73504	11.6454	9.88322	8.4124	6.21979	8.01304	5.96194	6.0688

Table 5: MSE values of 10 values for each Left, Right, Up and Straight Sample (Pupil, Sclera and ROI)

	Sample Number	Pupil				ROI				Sclera			
		Left	Right	Up	Straight	Left	Right	Up	Straight	Left	Right	Up	Straight
Gaussian Filter	1	490.27	499.395	577.619	33.8859	1326.21	1182.62	1597.54	325.792	0.162623	0.116847	0.0795475	0.405618
	2	323.112	249.575	285.524	282.292	578.78	799.868	548.95	524.336	0.139261	0.235375	665.501	0.121319
	3	214.143	831.58	311.696	363.094	817.818	1697.11	848.025	718.749	0.159257	0.0995702	0.150232	0.280016
	4	430.843	355.754	249.482	481.173	1143.16	1819.23	973.709	2056.28	0.0609849	0.0761761	0.167764	0.0655909
	5	427.493	266.345	983.896	331.337	1119.85	387.511	1733.79	536.165	0.109593	0.442951	0.118296	0.627762
	6	824.719	643.838	439.689	688.552	1957.93	717.117	924.365	1458.66	0.0299748	0.0889925	0.0602836	0.0542234
	7	183.832	354.857	331.464	1048.7	884.454	555.676	642.546	2078.16	0.172203	0.303449	0.199891	0.0963259
	8	460.553	110.323	474.302	186.137	1152.48	929.599	1988.64	1183.98	0.0666403	0.0723713	0.0692035	0.147288
	9	641.618	488.929	314.845	451.774	1458.93	1450.65	568.056	442.846	0.0317982	0.0423728	0.175152	0.258431
	10	7320.72	110.896	419.366	424.903	841.773	430.951	647.229	906.727	0.103596	0.108471	0.16213	0.148472
Average Filter	1	2700.12	2746.26	3181.88	185.111	7305.32	6510.3	8800	1793.44	1.01639	0.725663	0.500666	3.15861
	2	1779.28	1371.32	1572.53	1558.3	3185.86	4405.38	3023.66	2885.92	0.880958	1.52934	4231.61	0.80868
	3	1180	4582.13	1716.34	2001.93	4502.23	9338.5	4670.14	3958.55	1.03187	0.643832	0.955839	1.83413
	4	2368.27	1956.34	1364.92	2652.46	6283.28	10020.6	5361.25	11324.7	0.392973	0.487368	1.0609	0.409943
	5	2356.64	1462.81	5414	1823.01	6155.21	2132.01	9542.44	2952.82	0.703978	2.85993	0.743641	3.95105
	6	4536.34	3547.95	2419.04	3794.75	10785.3	3946.45	5086.64	8033.95	0.191959	0.567198	0.381353	0.341122
	7	1008.26	1950.3	1829.12	5773.83	4863.76	3058.75	3538.56	11444.6	1.11306	1.89655	1.2578	0.618198
	8	2531.54	606.415	2610.18	1024.17	6340.97	5112.64	10956.4	6519.22	0.426359	0.455108	0.442187	0.967151
	9	3537	2698.91	1730.36	2485.72	8036.88	7992.76	3128.22	2436.06	0.203635	0.270435	1.10298	1.4987
	10	3904.8	604.343	2308.26	2339.63	4636.5	2372.72	3561.76	4994.37	0.656133	1.01072	1.03963	0.933668
Circular Average Filter	1	5070.33	5156.67	5969.33	347.089	13710.2	12212.7	16515.8	3364.98	1.16579	0.84084	0.580659	3.31906
	2	3339.88	2570.93	2950.24	2918.15	5977.98	8268.31	5673.08	5412.57	1.01294	1.74848	5038.43	0.914453
	3	2211.43	8591.66	3213.68	3757.76	8447.19	17519	8763.78	7428.43	1.16493	0.733573	1.09641	2.08517
	4	4444.72	3673.12	2552.6	4964.47	11777.6	18806.3	10060	21255.8	0.447119	0.551703	1.21503	0.473113
	5	4422.82	2749.51	10154.9	3424.09	11538.4	3999.6	17901.4	5541.44	0.813286	3.2804	0.859609	4.58259
	6	8498.74	6656.27	4531.38	7122.82	20243.4	7402.16	9540.7	15080.8	0.220836	0.651126	0.438483	0.391937
	7	1893.59	3661.78	3426.1	10827.4	9119.02	5739.43	6640.62	21470.5	1.26644	2.17724	1.45175	0.705692
	8	4751.71	1137.4	4891.99	1925.72	11891.8	9586.77	20563.8	12231.6	0.487929	0.524588	0.507615	1.10126
	9	6640.38	5065.34	3245.51	4667.69	15084.4	15000.6	5870.45	4566.12	0.23076	0.309301	1.25733	1.7912
	10	708.947	1125.56	4329.31	4389.48	8701.15	4451.84	6679.73	9372.18	0.755218	0.959199	1.19043	1.07621

Table 6: SSIM values of 10 values for each Left, Right, Up and Straight Sample (Pupil, Sclera and ROI)

	Sample Number	Pupil				ROI				Sclera			
		Left	Right	Up	Straight	Left	Right	Up	Straight	Left	Right	Up	Straight
Gaussian Filter	1	0.948829	0.949123	0.94829	0.961023	0.945999	0.946037	0.945815	0.949077	0.945813	0.945806	0.945826	0.946111
	2	0.949555	0.94859	0.949472	0.949495	0.946896	0.946594	0.946892	0.9471	0.945715	0.945838	0.93032	0.945763
	3	0.951938	0.948664	0.950429	0.948941	0.94677	0.9458	0.946969	0.946663	0.945975	0.94564	0.945792	0.945775
	4	0.950047	0.951613	0.951556	0.949422	0.945802	0.945797	0.946304	0.945711	0.945781	0.945717	0.945719	0.945657
	5	0.952826	0.9514	0.947429	0.950692	0.945928	0.950144	0.945796	0.947125	0.945831	0.945831	0.945656	0.945813
	6	0.947039	0.949349	0.949603	0.948088	0.945742	0.94656	0.946168	0.945901	0.945662	0.945802	0.945838	0.945798
	7	0.9566	0.951236	0.953511	0.949111	0.946418	0.947218	0.947112	0.945719	0.945875	0.945792	0.945816	0.945595
	8	0.951181	0.957313	0.94987	0.955202	0.946042	0.946525	0.94577	0.946267	0.945778	0.945814	0.945649	0.945705
	9	0.948351	0.948512	0.951279	0.952075	0.945899	0.945928	0.947263	0.94926	0.945819	0.945813	0.945843	0.946006
	10	0.947223	0.957903	0.94969	0.949692	0.94665	0.948828	0.9466	0.946526	0.945842	0.946037	0.945749	0.945811
Average Filter	1	0.669124	0.670404	0.664544	0.753962	0.648341	0.648974	0.64714	0.669947	0.64824	0.648162	0.648335	0.650809
	2	0.675124	0.668581	0.672511	0.671929	0.654818	0.652471	0.654511	0.656259	0.647645	0.648498	0.608356	0.648044
	3	0.692542	0.667105	0.681343	0.669709	0.653896	0.647323	0.65506	0.653013	0.649761	0.647082	0.647975	0.647985
	4	0.678829	0.688222	0.69048	0.673415	0.648164	0.647069	0.650609	0.646525	0.648291	0.647486	0.647749	0.647101
	5	0.694745	0.685816	0.660318	0.67993	0.649604	0.678699	0.647302	0.656221	0.648751	0.648294	0.647261	0.648358
	6	0.657783	0.672902	0.673838	0.663536	0.646652	0.652787	0.649977	0.64779	0.647227	0.648222	0.64851	0.648081
	7	0.721883	0.686158	0.699284	0.67129	0.652508	0.657158	0.65614	0.646565	0.648839	0.647968	0.64821	0.646752
	8	0.686495	0.728362	0.676676	0.714144	0.649463	0.653193	0.646801	0.650352	0.648206	0.648378	0.64702	0.647546
	9	0.665346	0.66565	0.686997	0.691181	0.647701	0.64785	0.657221	0.672082	0.648251	0.648155	0.648569	0.650253
	10	0.658516	0.733931	0.674315	0.67449	0.652825	0.668143	0.652965	0.651916	0.648365	0.650373	0.647961	0.648194
Circular Average Filter	1	0.376631	0.380171	0.370568	0.527959	0.341886	0.343554	0.339821	0.379433	0.34002	0.339875	0.340104	0.344503
	2	0.388965	0.376161	0.384524	0.383774	0.352773	0.34865	0.352215	0.355698	0.339226	0.340435	0.279573	0.339864
	3	0.420236	0.375881	0.399966	0.377482	0.351724	0.341425	0.353816	0.349707	0.342488	0.338395	0.339581	0.33968
	4	0.396357	0.412444	0.414041	0.38795	0.34307	0.339748	0.346096	0.338818	0.34029	0.338925	0.339417	0.338387
	5	0.425281	0.40706	0.36426	0.395844	0.346036	0.394803	0.341122	0.355109	0.340964	0.339976	0.338664	0.34015
	6	0.359092	0.384567	0.387569	0.367994	0.339006	0.349725	0.344985	0.340782	0.338567	0.340043	0.340463	0.339702
	7	0.472497	0.408735	0.433656	0.384671	0.351182	0.357032	0.947112	0.339589	0.340887	0.339576	0.339889	0.337814
	8	0.408506	0.484275	0.392151	0.457504	0.344823	0.351923	0.339308	0.345514	0.340091	0.340343	0.33822	0.339088
	9	0.371524	0.372529	0.408428	0.418093	0.34067	0.340981	0.357212	0.384693	0.339917	0.339789	0.340524	0.343436
	10	0.359571	0.490189	0.387447	0.389547	0.34947	0.376593	0.350198	0.347935	0.340132	0.343392	0.339694	0.339827

Table 7: SNR values of 10 values for each Left, Right, Up and Straight Sample (Pupil, Sclera and ROI)

	Sample Number	Pupil				ROI				Sclera			
		Left	Right	Up	Straight	Left	Right	Up	Straight	Left	Right	Up	Straight
Gaussian Filter	1	42.4529	42.2927	41.0288	65.6612	33.8093	34.8047	32.1926	46.0028	32.5292	32.4004	32.5588	37.0911
	2	46.0745	48.3176	47.1488	47.2476	41.0113	38.2012	41.471	41.8694	31.5426	33.1935	27.1583	32.5209
	3	49.6475	37.8635	46.387	45.0612	38.0085	31.6674	37.6934	39.1301	35.3244	30.3009	32.0522	32.2677
	4	43.5752	45.2386	48.3208	42.6156	35.0995	31.0638	36.493	30	32.72	30.8041	31.7078	30.0123
	5	43.643	47.7527	36.4026	45.8562	35.2784	44.4959	31.4817	41.6756	33.7079	32.6353	30.7592	32.9583
	6	37.9355	40.0861	43.3987	39.5029	30.4257	39.1498	36.9447	32.9825	30.2873	32.5671	32.9357	32.1174
	7	50.9732	45.2605	45.8529	35.8486	37.3281	41.3652	40.1035	29.908	33.6548	32.2088	32.5327	29.3133
	8	42.996	55.4083	42.7405	50.8649	35.0289	36.8957	30.2905	34.7947	32.4602	32.8737	29.7868	31.1979
	9	40.1161	42.4767	46.2997	43.1632	32.9809	33.0304	41.1738	43.3365	32.4158	32.2732	33.2463	36.409
	10	39.2493	55.3633	43.8098	43.6958	37.7577	43.5731	40.0405	37.1121	32.7287	36.2979	32.2068	32.4263
Average Filter	1	27.6339	27.4868	26.2079	50.913	18.9888	19.9896	17.372	31.1879	17.7334	17.6034	17.7636	22.3142
	2	31.2567	33.5188	32.3296	32.4086	26.1971	23.3819	26.6509	27.0559	16.7478	18.3996	12.8574	17.7281
	3	34.824	23.0402	31.5695	30.2326	23.1931	16.8561	22.875	24.3109	20.5387	15.5045	17.2541	17.4713
	4	28.773	30.4327	33.5595	27.7886	20.2979	16.2437	21.6763	15.1811	17.9286	16.0056	16.914	15.2137
	5	28.8158	32.9578	21.5912	31.0458	20.4767	29.6858	16.6684	26.8569	18.9193	17.8375	15.964	18.1658
	6	23.1275	25.2621	28.5888	24.6779	15.605	24.3375	22.133	18.163	15.4901	17.7727	18.1419	17.3201
	7	36.1901	30.4596	31.0168	21.0323	22.5222	26.5507	25.2851	15.0896	18.8625	17.4096	17.7356	14.517
	8	28.1939	40.6062	27.9282	36.0541	20.2185	22.0887	15.4682	19.9777	17.6672	18.0799	14.9879	16.402
	9	25.2889	27.6378	31.4989	28.3526	18.1599	18.2077	26.3557	28.5278	17.6193	17.4755	18.4528	21.6291
	10	24.4296	40.6359	28.9959	28.8787	22.9378	28.7567	25.2283	22.292	17.9314	21.518	17.4136	17.6298
Circular Average Filter	1	22.1609	22.0142	20.7431	45.4528	13.5208	14.5254	11.9036	25.722	12.2423	12.1126	12.2717	16.8284
	2	25.787	28.0598	26.8637	26.9594	20.7305	17.9133	21.1852	21.5935	11.2584	12.9085	7.70907	12.2384
	3	29.3681	17.5801	26.1216	24.763	17.7274	11.3914	17.4078	18.8437	15.0476	10.0165	11.7635	11.9806
	4	23.3047	24.9609	28.1219	22.3442	14.8405	10.7755	16.2097	9.71207	12.4393	10.5168	11.4249	9.72553
	5	23.3476	27.4765	16.1281	25.5707	15.0187	24.2213	11.2039	21.3891	13.4291	12.3459	10.4757	12.6734
	6	17.6745	19.797	23.137	19.2086	10.1359	18.8744	16.67	12.6931	10.0017	12.2822	12.6507	11.8288
	7	30.7159	24.9878	25.5656	15.5712	17.0626	21.0842	19.8174	9.62478	13.3701	11.9188	12.2441	9.02841
	8	22.7246	35.1433	22.4719	30.5697	14.7566	16.6282	9.99953	14.512	12.1776	12.5898	9.49948	10.9135
	9	19.8178	22.1694	26.036	22.8796	12.691	12.7394	20.8882	23.0707	12.1271	11.9837	12.9611	16.139
	10	18.9705	35.2342	23.5332	23.4133	17.4701	23.2908	19.7664	16.8248	12.4396	16.0261	11.9239	12.1376

Table 8: AD values of 10 values for each Left, Right, Up and Straight Sample (Pupil, Sclera and ROI)

	Sample Number	Pupil				ROI				Sclera			
		Left	Right	Up	Straight	Left	Right	Up	Straight	Left	Right	Up	Straight
Gaussian Filter	1	19.94	19.1432	22.7311	5.11324	35.8497	33.6628	39.7667	16.9074	39.0132	39.3416	38.93	29.7553
	2	16.4446	14.9251	16.0183	15.5862	23.1178	27.2312	22.9448	21.7316	41.2771	37.6271	51.4444	39.0537
	3	12.3913	25.348	15.5296	17.592	27.4737	39.8857	27.4047	26.208	33.1314	44.3086	40.201	39.6796
	4	17.2723	16.5837	13.7136	19.2798	33.1897	41.8825	30.0722	44.6427	38.4457	42.9542	40.8281	44.9329
	5	17.5978	14.9559	28.4288	16.4596	32.2402	17.4753	40.5125	22.4474	36.4147	38.8449	43.1817	38.1515
	6	26.8043	21.7186	18.3239	24.3372	43.5776	25.8822	29.9197	37.7829	44.174	38.9256	38.032	39.9817
	7	11.5154	16.6669	15.5137	28.0458	28.1502	22.7733	24.3431	44.5672	36.5852	39.8598	39.1317	46.9248
	8	17.5104	8.3214	19.7377	19.7377	32.8971	28.8514	43.6853	32.6205	39.0496	38.194	45.5457	42.0322
	9	23.6195	20.4463	14.99	17.6969	37.9051	37.6795	22.9644	18.6815	39.3351	39.6609	37.4941	31.1681
	10	24.657	6.92256	18.1615	18.3181	27.7548	19.0488	24.7319	28.9133	38.6345	31.3456	39.7294	39.3245
Average Filter	1	46.7885	44.9167	53.3497	11.97	84.1538	79.0178	93.3447	39.6844	91.4509	92.228	91.2512	69.741
	2	38.5887	34.9867	37.6045	36.6395	54.2613	63.9202	53.8639	51.0171	96.7623	88.1954	115.556	91.5493
	3	29.0758	59.5237	36.4729	41.2956	64.4854	93.6131	64.3277	61.5192	77.6468	103.872	94.2435	93.0179
	4	40.5071	38.8968	32.1524	45.3256	77.8999	98.3056	70.5908	104.775	90.1134	100.7	95.7032	105.342
	5	41.3472	35.0666	66.6978	38.642	75.6655	41.0148	95.0952	52.6926	85.3416	91.0609	101.227	89.4165
	6	62.9234	50.9775	43.045	57.1299	102.289	60.7501	70.234	88.68	103.561	91.245	89.1445	93.7243
	7	26.9858	39.0783	36.4455	65.8443	66.077	53.4447	57.1375	104.614	85.7476	93.4498	91.7299	110.002
	8	41.0566	19.5154	46.3039	46.3039	77.2204	67.7186	102.549	76.5675	91.5322	89.53	106.777	98.5338
	9	55.453	48.05	35.1973	41.5146	88.9734	88.4514	53.9049	43.8608	92.2021	92.9713	87.8813	73.0359
	10	57.8435	16.2698	42.6261	42.9792	65.1499	44.7146	58.064	67.8736	90.5663	73.449	93.1281	92.1795
Circular Average Filter	1	64.1299	61.542	73.0783	16.4047	115.295	108.258	127.888	54.372	125.464	126.53	125.195	95.714
	2	52.8851	47.9359	51.5079	50.1557	74.3478	87.5796	73.7906	69.8954	132.75	120.999	159.778	125.607
	3	39.8301	81.5304	49.9442	56.5978	88.3503	128.26	88.1375	84.2856	106.554	142.485	129.288	127.614
	4	55.4979	53.2981	44.06	62.03	106.729	134.683	96.7176	143.552	123.633	138.135	131.293	144.499
	5	56.6411	48.0774	91.3605	52.9659	103.667	56.2019	130.291	72.194	117.094	124.932	138.864	122.684
	6	86.2065	69.8326	58.9575	78.2823	140.148	83.2285	96.2254	121.507	142.062	125.185	122.306	128.581
	7	37.0017	53.5529	49.8818	90.1815	90.5329	73.2228	78.2846	143.316	117.654	128.202	125.846	150.893
	8	56.2798	26.7252	63.4263	63.4263	105.8	92.7807	140.499	104.9	125.577	122.832	146.466	135.168
	9	75.9867	65.8343	48.2456	56.8868	121.901	121.181	73.8582	60.0927	126.496	127.548	120.575	100.234
	10	79.2098	22.3039	58.3797	58.8634	89.2599	61.2634	79.553	92.989	124.252	100.806	127.767	126.468

Table 9: SC values of 10 values for each Left, Right, Up and Straight Sample (Pupil, Sclera and ROI)

	Sample Number	Pupil				ROI				Sclera			
		Left	Right	Up	Straight	Left	Right	Up	Straight	Left	Right	Up	Straight
Gaussian Filter	1	1.59984	1.60117	1.60053	1.56449	1.60493	1.60502	1.60566	1.59646	1.60559	1.60558	1.60557	1.60454
	2	1.59622	1.59461	1.59483	1.59462	1.60075	1.60245	1.59977	1.60048	1.60628	1.60529	1.68254	1.60583
	3	1.59421	1.60367	1.59772	1.59664	1.60301	1.60723	1.60328	1.60163	1.60451	1.60682	1.60568	1.60568
	4	1.60084	1.59804	1.59919	1.60105	1.60603	1.60634	1.60395	1.60687	1.60583	1.60644	1.60621	1.60685
	5	1.59944	1.59472	1.60496	1.59693	1.60609	1.59916	1.60706	1.5997	1.60531	1.60537	1.60664	1.60548
	6	1.60518	1.60222	1.60164	1.60154	1.60659	1.60238	1.60375	1.60529	1.60682	1.60567	1.60547	1.60568
	7	1.59323	1.59795	1.59755	1.60561	1.60477	1.60031	1.60121	1.60738	1.60507	1.60556	1.60542	1.6072
	8	1.60187	1.58806	1.60053	1.59167	1.60543	1.60481	1.60662	1.60507	1.60585	1.60555	1.60693	1.60639
	9	1.60077	1.59873	1.59869	1.60064	1.60519	1.60514	1.60035	1.60098	1.60549	1.60554	1.60523	1.60411
	10	1.60248	1.59934	1.59924	1.59929	1.60285	1.59918	1.6017	1.60324	1.60531	1.60419	1.60593	1.60551
Average Filter	1	3.86573	3.872	3.87274	3.54469	3.91131	3.9084	3.91811	3.83342	3.90648	3.90693	3.90598	3.8859
	2	3.83334	3.81123	3.8225	3.82842	3.87078	3.8886	3.86529	3.8674	3.91184	3.90308	4.18981	3.90704
	3	3.8174	3.90139	3.84487	3.84199	3.89114	3.92516	3.8949	3.88134	3.89216	3.91765	3.9084	3.9076
	4	3.86716	3.84458	3.83108	3.8786	3.90993	3.92396	3.89985	3.92806	3.90638	3.91516	3.91106	3.91888
	5	3.86547	3.81129	3.90715	3.83683	3.91025	3.85464	3.92526	3.86412	3.90079	3.90552	3.91546	3.90412
	6	3.90608	3.88892	3.87566	3.88359	3.92636	3.88411	3.89623	3.91425	3.91787	3.90637	3.90446	3.90801
	7	3.79306	3.84133	3.8532	3.91486	3.90028	3.86718	3.8768	3.93106	3.9003	3.90785	3.90577	3.92094
	8	3.8756	3.7569	3.86807	3.79127	3.90935	3.90181	3.92743	3.91039	3.90738	3.9051	3.91969	3.91357
	9	3.87775	3.86445	3.84576	3.86925	3.91417	3.91447	3.86896	3.86742	3.90612	3.90709	3.90233	3.88609
	10	3.88944	3.81293	3.85842	3.86016	3.89217	3.85732	3.87809	3.90485	3.90485	3.88645	3.90842	3.90631
Circular Average Filter	1	9.37598	9.40753	9.39616	7.80957	9.60489	9.59239	9.63991	9.20326	9.6332	9.6354	9.63223	9.54327
	2	9.20738	9.08504	9.14084	9.14197	9.39788	9.48784	9.36173	9.37845	9.66163	9.61591	11.7035	9.6388
	3	9.10484	9.53544	9.24124	9.24647	9.50131	9.6863	9.52231	9.44814	9.56744	9.68683	9.64086	9.63897
	4	9.37647	9.26456	9.18503	9.40289	9.60315	9.67044	9.54874	9.69388	9.63406	9.67354	9.65576	9.69256
	5	9.3663	9.11534	9.57915	9.23183	9.60605	9.31574	9.68505	9.36034	9.60609	9.62815	9.67698	9.62473
	6	9.57561	9.47876	9.41742	9.4606	9.68542	9.46367	9.52747	9.62307	9.68913	9.63379	9.62418	9.64044
	7	9.0111	9.24978	9.2608	9.61656	9.55531	9.37646	9.42661	9.70917	9.6053	3.90785	9.62858	9.70484
	8	9.43087	8.80258	9.3615	9.02073	9.60034	9.56246	9.68971	9.59992	9.63816	9.62699	9.69642	9.66667
	9	9.43341	9.36142	9.27877	9.39262	9.61935	9.61948	9.38822	9.3847	9.63148	9.63561	9.61373	9.53837
	10	9.46789	9.08414	9.31548	9.32911	9.50552	9.32785	9.43353	9.62457	9.62457	9.54374	9.64339	9.63306

Table 10: MD values of 10 values for each Left, Right, Up and Straight Sample (Pupil, Sclera and ROI)

	Sample Number	Pupil				ROI				Sclera			
		Left	Right	Up	Straight	Left	Right	Up	Straight	Left	Right	Up	Straight
Gaussian Filter	1	34	39	32	14	61	60	59	32	64	64	63	68
	2	28	37	26	33	77	53	41	80	68	68	75	71
	3	30	48	62	30	57	68	57	51	70	72	68	66
	4	38	30	75	62	75	69	56	73	70	68	70	70
	5	42	26	47	30	71	52	66	42	67	66	70	71
	6	75	55	59	37	72	51	75	62	70	66	70	64
	7	27	31	29	60	54	49	48	75	64	61	70	75
	8	58	24	45	23	71	77	73	63	68	71	72	68
	9	34	33	54	36	58	59	46	44	62	71	62	72
	10	38	72	35	35	56	68	84	55	66	72	71	65
Average Filter	1	80	90	76	33	122	153	127	68	155	157	143	157
	2	66	78	60	80	177	132	89	164	166	155	190	157
	3	71	114	151	70	128	170	143	129	154	178	169	151
	4	89	70	188	151	177	174	129	183	165	172	171	175
	5	103	61	116	71	145	130	169	106	153	155	173	149
	6	190	131	148	86	184	125	183	157	157	154	166	153
	7	62	72	69	146	135	124	122	188	156	150	148	190
	8	137	56	108	55	179	167	185	160	172	163	182	164
	9	80	78	122	85	147	148	116	110	142	155	151	155
	10	91	182	82	82	142	160	184	140	151	159	157	163
Circular Average Filter	1	110	123	103	45	168	164	174	93	189	187	185	195
	2	87	106	82	101	208	142	113	214	193	194	203	197
	3	96	149	182	95	169	184	153	139	196	194	194	187
	4	122	96	202	183	199	186	170	196	193	192	194	191
	5	130	82	141	96	196	141	191	113	188	188	195	195
	6	203	175	179	115	196	141	205	168	197	191	197	186
	7	85	99	93	182	152	133	130	202	189	187	194	203
	8	175	76	139	71	196	209	198	179	191	196	195	190
	9	109	106	162	114	157	159	124	123	185	196	188	195
	10	122	194	112	112	152	195	217	150	192	200	198	189

Table 11: LMSE values of 10 values for each Left, Right, Up and Straight Sample (Pupil, Sclera and ROI)

	Sample Number	Pupil				ROI				Sclera			
		Left	Right	Up	Straight	Left	Right	Up	Straight	Left	Right	Up	Straight
Gaussian Filter	1	0.242461	0.262162	0.277384	0.303187	0.2092	0.202301	0.217277	0.211792	0.223236	0.226263	0.213852	0.191734
	2	0.241458	0.253773	0.263022	0.236241	0.201795	0.212079	0.21649	0.206094	0.214985	0.23097	0.223373	0.216265
	3	0.219373	0.228732	0.227098	0.263818	0.206132	0.17123	0.210357	0.220117	0.218383	0.220713	0.229131	0.226097
	4	0.245127	0.260358	0.224431	0.240975	0.198056	0.224552	0.187172	0.22171	0.215927	0.218938	0.221909	0.217353
	5	0.230952	0.254571	0.21965	0.256203	0.195097	0.219592	0.192827	0.219509	0.217966	0.236175	0.218929	0.217575
	6	0.33423	0.238395	0.246734	0.269157	0.223683	0.214414	0.209244	0.219364	0.218913	0.213933	0.213052	0.226915
	7	0.239373	0.231331	0.271015	0.221199	0.192554	0.213698	0.207299	0.185684	0.221151	0.220414	0.239292	0.221186
	8	0.234318	0.280605	0.220208	0.279237	0.208095	0.209249	0.222337	0.206717	0.221261	0.219961	0.216196	0.220865
	9	0.254724	0.240761	0.214608	0.252299	0.232759	0.234845	0.212544	0.213845	0.229241	0.226624	0.223964	0.224722
	10	0.276414	0.228003	0.257083	0.236148	0.211688	0.200649	0.208426	0.214232	0.232944	0.21295	0.222911	0.231035
Average Filter	1	0.819549	0.897022	1.0226	0.876096	0.761251	0.755913	0.779236	0.755391	0.801788	0.813373	0.778476	0.720812
	2	0.82972	0.864871	0.835554	0.846601	0.744001	0.766807	0.770531	0.763533	0.788038	0.826294	1.29047	0.791538
	3	0.792107	0.812526	0.808182	0.844919	0.759244	0.677849	0.769135	0.788659	0.799194	0.805005	0.820645	0.822277
	4	0.863867	0.878088	0.812204	0.943465	0.748609	0.808592	0.712297	0.80762	0.791719	0.794828	0.808224	0.792376
	5	0.821295	0.829067	0.792646	0.872035	0.739427	0.79426	0.731935	0.777497	0.798314	0.855631	0.803028	0.845044
	6	1.14419	0.811318	0.992393	0.856228	0.811353	0.784364	0.771703	0.787531	0.796283	0.783669	0.779113	0.810832
	7	0.824362	0.843394	0.873148	0.822341	0.732891	0.774933	0.747247	0.709428	0.801235	0.80739	0.846157	0.803328
	8	0.833656	0.877694	0.814919	0.872316	0.769652	0.771618	0.812737	0.763554	0.802934	0.801897	0.788407	0.803342
	9	0.837557	0.854006	0.80246	0.843267	0.81829	0.828131	0.771427	0.780148	0.808788	0.799854	0.806076	0.821841
	10	0.924488	0.812431	0.834593	0.809952	0.760407	0.730852	0.771385	0.773909	0.823395	0.78065	0.810395	0.824417
Circular Average Filter	1	1.00653	1.03006	1.06795	1.09183	0.988346	0.984011	0.998392	0.983652	1.00609	1.00803	0.998011	0.988112
	2	0.993113	1.02165	1.05724	1.01513	0.989521	0.987535	0.99637	0.991508	0.998052	1.01142	1.01509	1.00846
	3	1.01135	1.01511	0.982622	1.06149	0.986712	0.95676	0.984313	0.998468	1.00814	1.00756	1.01095	1.01326
	4	1.01597	1.04162	0.999496	1.02245	0.986064	1.00697	0.969236	0.997608	1.00635	1.00652	1.01127	1.00336
	5	1.03674	1.0271	1.01601	1.03517	0.98505	1.00112	0.978095	0.998795	1.01229	1.02955	1.01004	1.00627
	6	1.03731	1.02167	1.01589	1.02761	1.00577	0.999732	0.999385	0.999543	1.00409	1.00052	1.00302	1.01061
	7	0.239373	1.05005	1.04085	1.00436	0.983446	0.991431	0.976024	0.956002	1.01015	1.02511	1.01647	1.00236
	8	1.00767	1.0994	0.999929	1.07453	0.987729	0.987219	1.00299	0.989426	1.00731	1.0068	1.00508	1.00873
	9	1.0719	1.03356	1.01286	1.0344	1.01364	1.01163	0.992042	0.987712	1.01613	1.00987	1.00714	1.01016
	10	1.0477	1.00158	1.06315	1.07576	0.976485	0.978353	1.00524	0.988702	1.01664	1.00232	1.01439	1.02195

Table 12: NAE values of 10 values for each Left, Right, Up and Straight Sample (Pupil, Sclera and ROI)

	Sample Number	Pupil				ROI				Sclera			
		Left	Right	Up	Straight	Left	Right	Up	Straight	Left	Right	Up	Straight
Gaussian Filter	1	0.208581	0.208471	0.209203	0.197118	0.210509	0.210352	0.210761	0.207795	0.21072	0.210718	0.210713	0.209985
	2	0.207815	0.20741	0.207597	0.207229	0.20917	0.209729	0.209133	0.208895	0.210839	0.210651	0.228642	0.210703
	3	0.206417	0.209553	0.207556	0.668891	0.209771	0.210787	0.209756	0.209606	0.210308	0.211003	0.210772	0.210748
	4	0.20816	0.207767	0.207324	0.208633	0.210359	0.210881	0.210031	0.211028	0.21069	0.210925	0.21083	0.211016
	5	0.207848	0.207167	0.210097	0.207573	0.210323	0.208113	0.210796	0.209041	0.210576	0.2107	0.210945	0.210702
	6	0.209958	0.208929	0.208334	0.209338	0.21095	0.209584	0.210058	0.210649	0.210981	0.210706	0.210658	0.210763
	7	0.205565	0.207796	0.207308	0.210016	0.209876	0.209143	0.209361	0.21101	0.210571	0.210747	0.210721	0.211109
	8	0.20816	0.202947	0.208773	0.205793	0.21031	0.209999	0.210948	0.210278	0.210721	0.21066	0.211049	0.210885
	9	0.209167	0.208474	0.207301	0.20812	0.210648	0.210624	0.209127	0.208356	0.210734	0.210749	0.210628	0.210153
	10	0.209644	0.201649	0.208181	0.208408	0.20979	0.208345	0.209467	0.209911	0.210683	0.210167	0.210761	0.210735
Average Filter	1	0.489426	0.489146	0.491	0.46145	0.494149	0.493767	0.49472	0.487728	0.493948	0.493983	0.493907	0.492168
	2	0.487506	0.486202	0.487353	0.487147	0.490936	0.492299	0.490948	0.490403	0.494252	0.493751	0.51358	0.493929
	3	0.484234	0.492047	0.486984	0.488044	0.492368	0.494724	0.492364	0.492016	0.492877	0.49465	0.494115	0.494041
	4	0.488077	0.487315	0.485032	0.490048	0.493685	0.494975	0.493023	0.495276	0.493839	0.494484	0.494195	0.494714
	5	0.488351	0.485739	0.492922	0.487315	0.493488	0.488076	0.494803	0.490699	0.493505	0.493926	0.4945	0.493828
	6	0.492764	0.490396	0.48919	0.491406	0.495161	0.491924	0.492997	0.494413	0.494619	0.493912	0.493769	0.494068
	7	0.481851	0.487211	0.487015	0.492741	0.49257	0.49082	0.491408	0.49531	0.493533	0.494089	0.493959	0.494885
	8	0.488073	0.475885	0.489771	0.482363	0.493632	0.492731	0.495188	0.49357	0.49393	0.493805	0.494782	0.494366
	9	0.491074	0.489927	0.486099	0.48822	0.494447	0.494433	0.49089	0.488908	0.493964	0.494029	0.493686	0.492448
	10	0.491809	0.47193	0.488614	0.489007	0.492449	0.489062	0.491673	0.492763	0.493878	0.492465	0.494036	0.493978
Circular Average Filter	1	0.670824	0.670197	0.67257	0.632407	0.677009	0.676484	0.677797	0.668241	0.677661	0.67771	0.677633	0.675461
	2	0.667946	0.666154	0.667541	0.666855	0.672671	0.674519	0.672572	0.671871	0.678071	0.677401	0.710123	0.677679
	3	0.662983	0.673716	0.207556	0.207908	0.674584	0.677827	0.674604	0.674097	0.676369	0.678529	0.67785	0.677787
	4	0.66869	0.667741	0.665269	0.670938	0.676385	0.678138	0.675499	0.678577	0.677534	0.678304	0.677977	0.678603
	5	0.668988	0.665963	0.675046	0.667955	0.676105	0.668946	0.677935	0.672306	0.677122	0.677646	0.678357	0.677558
	6	0.675024	0.67178	0.669953	0.673349	0.678428	0.673944	0.675462	0.677433	0.678506	0.67763	0.677449	0.677816
	7	0.660647	0.667674	0.666563	0.675029	0.674876	0.672456	0.673282	0.678552	0.677177	0.677828	0.67767	0.678851
	8	0.669042	0.651652	0.670895	0.661762	0.676309	0.675088	0.678444	0.676211	0.677643	0.677484	0.67869	0.678169
	9	0.672915	0.67126	0.66677	0.669	0.677432	0.677387	0.672595	0.669817	0.677691	0.677763	0.677347	0.675829
	10	0.673475	0.648187	0.669193	0.669738	0.674689	0.670062	0.673545	0.675101	0.677572	0.675891	0.67779	0.677723

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