ISVM BASED TEMPLATE MATCHING OF RETINA IMAGES

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Abstract: Nowadays, the development of automatic retinal diseases diagnosis systems based on image processing has shown their potential for clinical practice. However, the accuracy of these systems is often compromised, mainly due to the intrinsic difficulty in detecting the abnormal structures and also due to deficiencies in the image acquisition which affects image quality. Further, with noise being present in the images, retinal matching is difficult to be analyzed. In this work new image denoising is performed based on the clustering algorithm. The proposed fuzzy clustering algorithm finds the similarity between the retina noisy and un-noisy pixels. From this noises presented in the samples are removed by using the fuzzy clustering. If the noises are removed from the samples then dimension reduction initializes the Mutual Information (MI) optimization as a coarse localization process, which narrows the optimization domain and avoids local optima. In addition, proposed work nearest template of the retina image is performed by using the Improved Support Vector Machine (ISVM) method has been used with area-based registration, providing a robust approach. To the best of knowledge, this is the first template matching algorithm for retina images with small template images from unconstrained retinal areas.

Keywords: Retina image template matching, Noise removal, Fuzzy clustering, Improved Support Vector Machine, teleophthalmology,dimension reduction, mutual information, healthmonitoring

1. INTRODUCTION

Teleophthalmology is gaining importance as an effective eye care delivery modality worldwide. In many developing countries, teleophthalmology is being utilized to provide quality eye care to the underserved urban population and the unserved remote rural population. Over the years, technological innovations have led to improvement in evidence and teleophthalmology has evolved from a research tool to a clinical tool. Teleophthalmology produces the same desired clinical outcome as the traditional system. Remote portals allow specialists to provide care over a larger region, thereby improving health outcomes and increasing accessibility of specialty care to a larger population. A high satisfaction level and acceptance is reported in the majority of the studies because of increased accessibility and reduced traveling cost and time. Considering the improved quality of patient care and patient satisfaction reported for these telemedicine services, this review explores how teleophthalmology helps to improve patient outcomes.

Teleophthalmology provides an easy, cost-effective way to diagnose many retinal diseases and ultimately to preserve a patient’s eyesight. In retina, there has been a trend toward teleophthalmology, particularly for diabetic retinopathy and retinopathy of prematurity (ROP) screenings, especially in areas where retinal specialists are not readily available. In this part, the challengingproblem of retinal image matching and registration has been addressed to enablefuture teleophthalmology applications.In [1] proposed a new method for localizing optic disc in retinal images. Localizing the optic disc and its center is the first step of most vessel segmentation, disease diagnostic, and retinal recognition algorithms. In [2]reviewed the current evidence on the critical features and characteristics of ocular telehealth programs for DR in the following categories: image gradability, mydriasis, sensitivity and specificity, cost-effectiveness, long-term effectiveness, patient comfort and satisfaction, and improvement of patient related outcomes. In [3]reviewed current trends in imaging for DR screening and emerging technologies that show potential for improving upon current screening approaches.

In [4] studied the cost benefit analysis of using a telemedicine-based digital retinal imaging evaluation compared to conventional ophthalmologic fundus examination of diabetic patients for diabetic retinopathy. In [5] analyzed the financial impact of ophthalmic telemedicine in a mountainous, rural health clinic in West Virginia over a seven year period from 2003-2009.In [6] determined whether tele-ophthalmology screening for proliferative diabetic retinopathy (PDR) can be cost-saving. In [7] suggested that primary care clinics can use telemedicine to screen for diabetic retinopathy and monitor for disease worsening over a long period.In [8] assesses patient preference for diabetic retinopathy (DR) screening with teleophthalmology or face-to-face ophthalmologist evaluation in Nairobi, Kenya. In [9] described the experience of using telemedicine technologies for ophthalmologic evaluation in diabetic and hypertensive patients presenting to a community health center in rural West Virginia.

In [10] compared the ability to identify nondiabetic retinal findings in patients with diabetes via either nonmydriatic fundus photography (NMFP) or Ultrawide Field Imaging (UWFI) in an established teleophthalmology program using

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validated methods of retinal imaging.In [11] proposed a method to detect artifacts inretinal images and mask the affected regions in order to avoid them from being considered for automated detection of retina pathologies. In [12] assessed the cost-effectiveness of a telemedicine diabetic retinopathy (DR) screening program in rural Southern India that conducts 1-off screening camps (i.e., screening offered once) in villages and to assess the incremental cost-effectiveness ratios of different screening intervals.In [13] demonstrated accuracy of a novel telehealth approach that may improve the diagnostic process for ASD; however, some limitations exist that should be considered when interpreting the findings.

In [14]examinedADSs feasibility and acceptance for promoting child learning throughout families' daily play and caretaking interactions at home.In [15] evaluated the reliability and feasibility of telehealth language assessments for school-aged children with autism.The findings suggests that telehealth may present a reliable and feasible approach to the assessment of language for children with autism in some circumstances as a primary or adjunct service model, while acknowledging that individual differences among these children may be important to consider when planning both assessment and intervention via telehealth. With that the eye provides a unique opportunity to image internalbiological tissue in vivo and many diseases can be diagnosedand monitored through ocular imaging.With this motivation, in this work, the timely detection of autism pathological changes via regularretinal screening and analysis is focused forearly diagnosis of autism disorder. The main contribution of the work is as follows:

- The input retina image is denoised using fuzzy clustering, where the fuzzy c-means is applied in the detection phase provides an optimum classification of noisy data and uncorrupted image data so that the pictorial information remains well preserved.
- The coares localization process is done using the Mutual Information to find the nearest target image in the low-dimensional space and that nearest target image is registered with MI
- The improved support vector machine is applied for the template matching by finding the nearest target image and the final result of diseases diagnosis process is carried out.

The rest of the work is structured as follows: an efficientand accurate retinal matching technique that combinesdimensionreductionand mutual information (MI) with preprocessing method of fuzzy c-means clustering with ISVM is proposed and explained in section 2. The experimental results with comparison among the existing and proposed method is discussed in section 3. Finally, the conclusion with the future work is depicted in section 4.

2. ISVM BASED TEMPLATE MATCHING OF RETINA IMAGES

Retina images captured by adapter-based optics provideless information and have low image quality, which furtherincreases the difficulty of template matching. In order to solve this issue the input retina images are denoised using fuzzy c-means clustering method. After that,the principal component analysis (PCA) used to localize the template image coarsely, thus the resultingdisplacement parameters are used to initialize the Mutual Information (MI) metricoptimization which is the initial parameters provided by the coarselocalization are in the convergence domain of MI metric. Another contribution is that this paperproposes an efficientImproved Support Vector Machine (ISVM) accelerates the matching ofoverlapped images among unordered data, which is the automated retinalimage matching and registration methodused foradvanced teleophthalmology and long-term retinal monitoring. The overall diagram of the proposed work is illustrated in Fig.1.

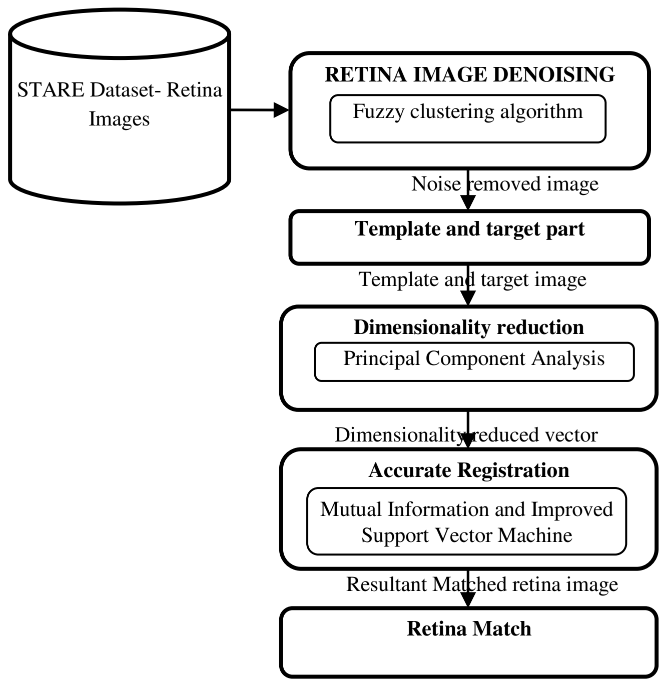

Fig.1. Overall Proposed Retina Matching Process

2.1. Retina Image Preprocessing Using Fuzzy Clustering

Retina Dataset: The proposed method is validated on the STARE retinaldataset [21] with synthetic deformations, and the in vivodata captured by a low-cost (<US$400) adapter-based opticaldevice D-eye. The performance of different dimensionreduction techniques are also compared on the STARE dataset.

The efficient removal of noise mainly depends on the detection phase. The detection method of the proposedalgorithm efficiently identifies the location of noisy pixels,so that the false alarm rate and miss detection rate areminimized. Using clustering, the high intensity and low intensity noisypixels are grouped separately. The rest of the pixels belongto the noise free group. In this technique for noise removal, the detection of impulse noise is done in two processes, first locates the noisy pixels and second maintains the valueof noise free pixels. The flowchart of proposed retina image denoising using fuzzy clustering is shown in Fig.2.

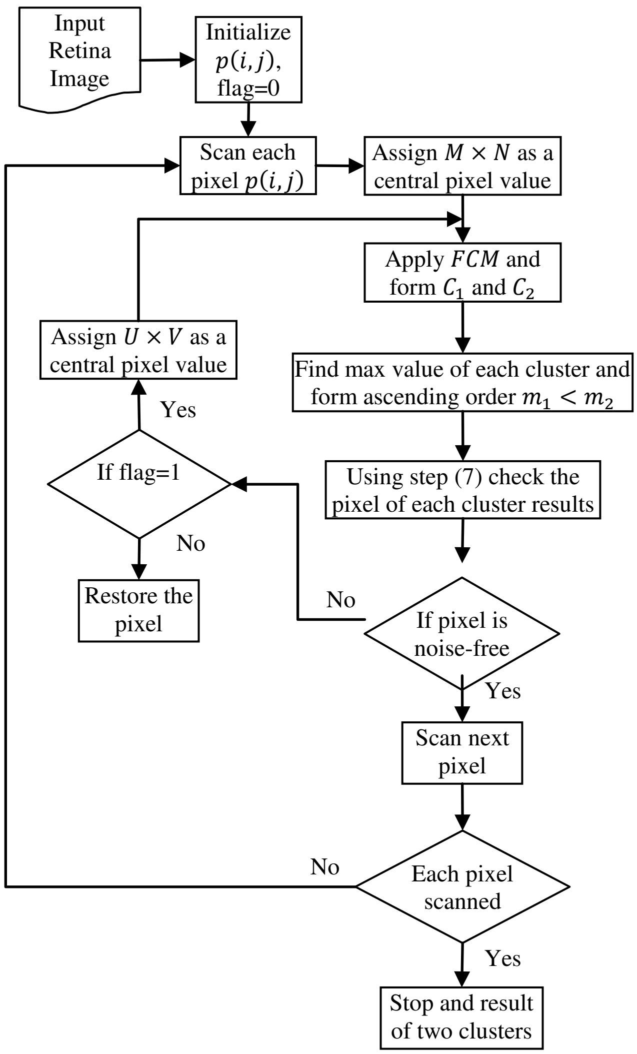

Fig.2.The Flowchart of Proposed Retina Image Denoising Using Fuzzy Clustering

1. **Process I: Location of noisy pixels detection**
2. Select a window size $M \times N$that can be centered on each pixel of retina image.
3. Let the central pixel at which window is centered be $p(i,j)$ using FCM algorithm, divide the neighborhoodvalues of the central pixel into two clusters.
4. Let the two clusters formed after applying FCM be C_1 and C_2. After the formation of clusters find the maximum value present in each cluster respectively.
5. In window there will be $M \times N = X$ values. The FCM algorithm divides these$X$ values unsupervisely into two clusters. Let the two maximum values present in these clusters bem_1 and m_2.
6. Them_1 and m_2 values from each cluster are sorted inascending order, such that $m_1 < m_2$.
7. Using the following equation, check whether the centralpixel$p(i,j)$is noisy or noise-free.

$$p(i,j) = \begin{cases} noise & if\ p(i,j) \le m_1 \\ noise\ free & if\ m_1 < p(i,j) \le m_2 \end{cases}$$

Where, pixels in the cluster having the minimum, maximum valuei.e. m_1 are lowest intensity pixels which contain the noise. The cluster having the maximum value as m_2 is considered asNoise free cluster.

8. If the pixel lies in a noise free cluster, it is left unaltered.
9. If the pixel is noisy it is processed again in the second detection stage.
10. **Process II: Location of noisy pixels detection**
11. Now change the window size to $U \times V$
12. Repeat Steps 3-7 in the same way up to the stopping criteria is met
13. If the pixel is detected as a noisy pixel in the seconddetection stage also, it is marked as noisy pixel else noisefree.
14. Restoration of noisy pixels is performed using the well known median filter. Median value forneighboring pixels within the window of size $U \times V$ is computedand is used to replace the noisy pixel value.

2.2. PCA for Location Estimation and Mutual Information

In this section, the combination of dimensionality reduction and mutual information based image registration. After the image denoising, dimension reduction methods allow the construction of low-dimensional summaries, while eliminating redundancies and noise in the data. To estimate the template locationin the 2d space, the full image dimension is redundancy, thus dimension reduction methods applied for the template coarse localization. In this section, PCA is selected as the dimension reduction method in RetinaMatch since it is simple and versatile.The full image can be a wide-field fundus image or a mosaicked one from D-eye images. Specifically, PCA forms a set of new variables as a weighted linear combination of the input variables and the detailed explanation is described in [17].

After that, the maximization of MI formultimodal image registration is described. The full image can be a wide-field fundus image ora mosaicked one from D-eye images. The optimizer used for the MI maximization is based onNewton's method. The MI function is a quasi-concave function, and the parabolic hypothesis of the Newtonsmethod is only valid near the convergence. When the initialtransformation on the convex part of the cost functions, this will cause the optimization to diverge. The proposed coarse localization provides a good initializationof the displacement for subsequent optimization of the MIcost function. The estimation is close to the optimal value andfalls in the convex domain of the MI metric, which providesmore efficient optimization and avoid local extrema.The underlying conceptis to use PCA and block PCA first for coarse localization,which can be a warm start to follow accurate registration.In accurate registration, the MI metric is optimized to find the optimal transformation. Since the optimization domain hasbeen narrowed to a small range near the optimal position withcoarse localization, the accurate registration can achieve highaccuracy and efficiency.

2.3. Proposed Template Matching Using ISVM

Much of the foundational work on template matching ofretinal images is based on more general image registrationmethods, which have been comprehensively studied in recentyears. However, general retina registration methods focuson matching image pairs that both have a large FOV withlocal deformations or different image modalities.In this section, a new templatematching method using ISVM is proposed to overcome the challenges posed byregistering small FOV and low-quality retinal images ontoa full image.The template-matching classifier operates on a set of templates, that is, supervectors, which can be defined a priori or selected by the user when the ISVM detects an abnormal sound that is not a normal retina.

Denoting by $\boldsymbol{x}$ the supervector of the input retinal images and with $\mathcal{Y} = \{\boldsymbol{y}_1, \ldots, \boldsymbol{y}_N\}$ the set of templates, the algorithm operates by calculating the Euclidean distance $D\ (i) = \|\boldsymbol{x} - \boldsymbol{y}_i\|$ between the supervector to be classified and all the templates in the set. Indicating with $D_{min} = \min_i D^{(i)}$, the supervector x is classified as a fall if $D_{\min} > \beta$ and as nonfall otherwise. The threshold β is a hyperparameter of the algorithm that can be determined on a validation set.Support Vector Machine (SVM) aims to adapt two or more classifiers of any kind to new datasets.

Problem is how to select best classifier for adaptation. Solution to this problem is to select classifier with best parameters after estimating performance of each classifier on sparsely labeled dataset. General problem of binary classification task is considered on original STARE retina image dataset D, which made up of majority of unlabeled instances D_u and limited numberof labeled instances D_l,therefore, the original dataset is$D = D_u \cup D_l$: There are one or more subordinate datasetsD_k^s, which is different from the original dataset. The subordinate classifierf_k is used to train each of the subordinate datasets D_k^s and $D_l = \{x_i, y_i\}_{i=1}^m$, where, x_i is the ith data vector and $y_i \in \{-1, +1\}$is its binary label. Data vectoralways include a constant 1 as its first element, such that, $x_i \in R^{d+1}$, where$d$ is the number of features.

There exist multiple subordinate datasets as $D_k^s, \forall k = 1, \ldots m$ with $D_k^s = \{x_i^k, y_i^k\}_i^{N_k}$. The subordinate dataset description is different from the original dataset. The subordinate classifier $f_k(x)$ has been trained from each subordinate dataset, which gives us the result of prediction of data label through the sign of its decision function, i.e. $\hat{y} = f^x(x)$. The traditional SVM trains the from the labeled dataset D_l. ISVM is used to adapt a combination of multiple existing classifiers $f_k^s(x), k = 1, \ldots, m$ to the new classifier. The traditional SVM trains the $f(x)$from the labeled dataset D_l. The decision boundary is determined by the kernel function $(x, x') = (\Phi(x), \Phi(x'))$, where $\Phi(x)$ is a feature vector. The kernel function is the inner product of two projected feature vectors. Delta function is used in ISVM in the form of $\Delta f(x) = w^T \Phi(x)$ on the basis of $f_k(x)$, where, $w$are the parameters predicted from the labeled data D_l. As defined earlier, the objective is to make a group of subordinate classifiers and adapt this group to new classifier $f(x)$, $f(x) = \sum_{k=1}^m t_k f_k(x) + \Delta f(x)$ Where,$t_k \in [0,1]$ is the weight of each subordinate classifier$f_k(x)$ which sums to one as .

1. **INPUT:** Input supervector $\boldsymbol{x}$, $\mathcal{Y} = \{\boldsymbol{y}_1, \ldots, \boldsymbol{y}_N\}$, label information,Error threshold =Huge value
2. **OUTPUT:** Set of support vectors,
3. Map images into space $Z = xW$
4. For each image X_i
5. Find the nearest 3 neighbors x minimizing the feature distance using Euclidean $d(Z_i, Z_j)$
6. Compute the Mutual Information between each $x_j$and x_i and take the adjacent image with highest MI.
7. Begin:
8. Randomly sample 2 points belonging to different classes are defined as $f_k(x)$. Add the m to the current set of support vectors.
9. Set the corresponding dual variables-"α"values
10. ISVM ()
11. {
12. LOOP Forever
13. LOOP to randomly sample 40 points.
14. Choose the set of 40 points with which current SVs give 40 pt test error less than the current error threshold.
15. Calculate kernel function to find the decision boundary
16. BREAKIF Points are insufficient.
17. ENDLOOP Random sampling of 40 points
18. BREAKIF the Inner LOOP is at QUIT because of insufficient points.
19. Update error threshold as the average of 40 pt test errors.
20. LOOP Over misclassified points.
21. Add the point to current SVs.
22. Train using ISVM with a warm start and test over the remaining points.
23. ENDLOOP over misclassified points.
24. ADD the misclassified point that gave the min-most error to the SVarray over the remaining points.
25. Save dual variable "α" s for the next iteration end loop FOREVER.
26. ISVM (); // SVM with kernel function
27. END.
28. Panorama R Mosaicking: Align all the adjacent images with mutual information based registration method.
29. Panorama blending.
30. return panorama R

Before entering the classification algorithm, use those two as input parameters. In this way, theadjacent images can be recognized and registered efficiently.For a series of small images x, we form the matrix x,as with the matrix T. PCA is applied to x and returns thelow-dimensional features for each image i. The distancebetween features in i indicates the distance between images.The nearest neighbor $x_j$of image $x_i$is the one with largestoverlap; the image pair is then registered with MI-basedapproach. To improve the algorithm robustness, the 3-nearestneighbors for each image are first selected to compute MIwith, and we keep the one with the largest metric value.The ISVM algorithm is designed as a recursive function, helping multi-image classification. During testing time, more than one image can be provided. The ISVM function is called recursively and provides output for all images. On the first call, the image is classified as affected or not affected. A further call furnishes the grade of the disease for affected images, input parameters being cotton wool spots and extracted vein pixels. Using these two parts, we can create models (database) for trained images and establish a clear classification of the testing time. The output is simply tagged to read "affected with (the grade of the disease)" or "not affected."

3. EXPERIMENTAL RESULTS AND DISCUSSION

We present the performance of our template matchingmethod on three experiments using retina images. For comparison,the ASIFT[18] andRetinaMatch[17] is used.In the first experiment, each template is extracted from thefull fundus image in the STARE dataset and matched back toit, which consists of 400 raw fundus images of healthy anddiseased retinas. Matching image pairs are simulated from thisdataset. Each image pair includes a full fundus image selectedrandomly from the dataset and an affine transformation isapplied to map it from a square into a parallelogram. Thearea within the mapped square is then cropped and warped (with the inverse affine transformation) to obtain the squaretemplate. The FOV of the template images is around 12witha size of 200×200 pixels. The template dimension is 10% ofthe full image.The output of the ISVM-RetinaMatchis compared with the existing models such as ASIFT and RetinaMatchwith the performance metrics of precision, recall, f-measure, and accuracy.

3.1. Precision Rate comparison

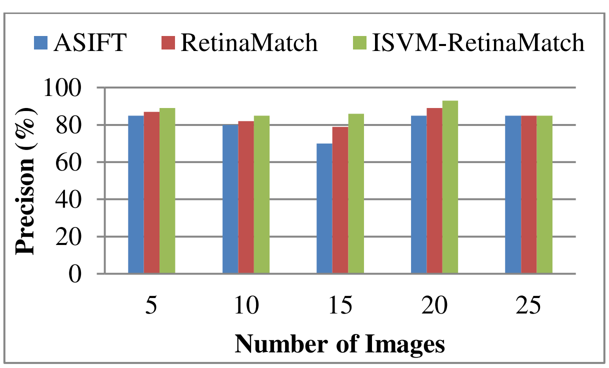

Fig.3. Result of Query matching-Precision Rate

From the above Fig.3, the graph explains that the precision comparison for the number of images in specified datasets. The methods are executed such asISVM-RetinaMatch, ASIFT and RetinaMatch.When number of images increasedaccording with the precision value is increased. From this graph, it is learnt that the proposed ISVM-RetinaMatch provides higher precision than the previous methods which produce better template matching results.

3.2. Recall Rate comparison

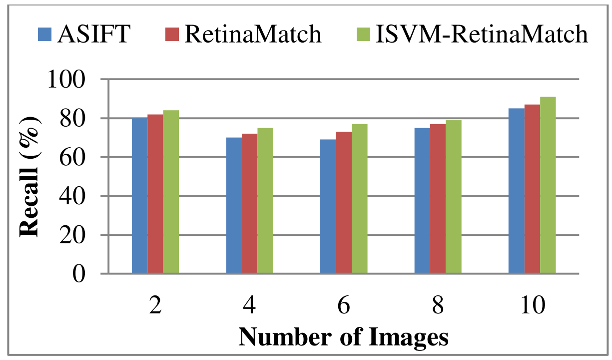

Fig.4. Result of Query matching-Recall Rate

From the above Fig.4, the graph explains that the recall comparison for the number of images in specified datasets. The methods are executed such asISVM-RetinaMatch, ASIFT and RetinaMatch. When number of images isincreasedcorresponding recall value is also increased. From this graph it is learnt that the proposed ISVM-RetinaMatch provides higher recall than the previous methods. The reason is that the fuzzy clustering produce the noise free images which will improve the nearest target detection results.

3.3. F-measure Rate comparison

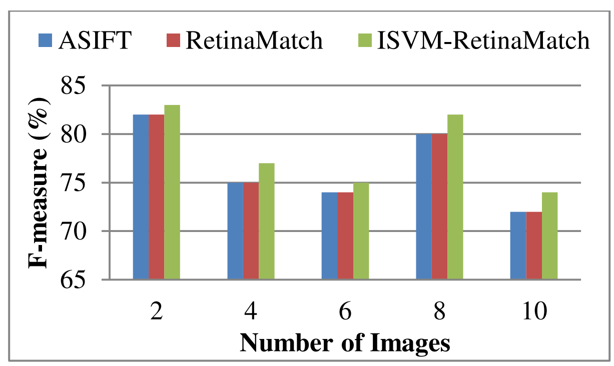

Fig.5. Result of Query matching-F-measure Rate

From the above Fig.5, the graph explains that the f-measure comparison for the number of images in specified datasets. The methods are executed such asISVM-RetinaMatch, ASIFT and RetinaMatch.When the number of images isincreased and the f-measure value is increased correspondingly. From this graph it is learnt that the proposed ISVM-RetinaMatch provides higher f-measure than the previous methods. Thus the proposed ISVM algorithm is greater to the existing algorithms in terms of better template matching results. The reason that the kernel function of SVM is improved with delta function which will improve the fetching template matching results.

3.4. Processing Time comparison

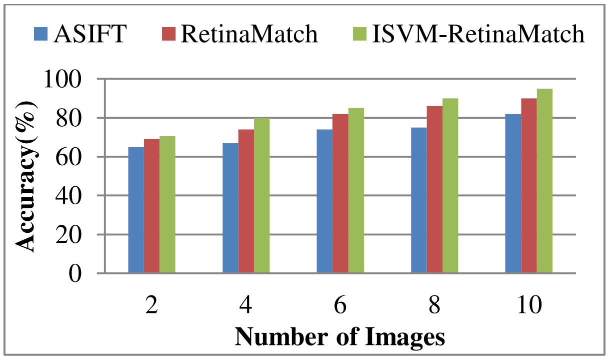

Fig.6. Result of Query matching-Processing Time

From the above Fig.6, the graph explains that the processing time comparison for the number of images in specified datasets. The methods are executed such asISVM-RetinaMatch, ASIFT and RetinaMatch.In x-axis the number of images is considered and in y-axis the accuracy value is considered.From this graph it is learnt that the proposed ISVM-RetinaMatchprovides lower processing time than the previous methods. Thus the output explains that the proposed ISVM-RetinaMatch algorithm is greater to the existing algorithms in terms of better template matching results with high accuracy rate. The reason is that existing approaches has a low rateof success as well, which has a high probability to cause misdetectionof emerging changes.

4. CONCLUSION AND FUTURE WORK

Finally, a new template matching method called RetinaMatch is proposed based on ISVM and fuzzy concept,which can be used in remote retina health monitoring withaffordable imaging devices. The application of FCM is used to detect the noisy pixels makesthis proposedRetinaMatchalgorithm a novel technique. A PCA-based coarse localizationmethod is proposed to provide a good initialization for the MIbasedregistration in the template matching.Matching the capturedimages onto the full retina image is done using ISVM, the hemorrhagic spotscan be easily segmented after the subtraction of the currentretina regions and previous status. In this way, RetinaMatchcan obtain an accurate affine transformation betweenthe image pair with poor quality and a large FOV baseline.By extensive simulationresults and comparison with existing methods such as ASIFT and RetinaMatch, it is observed thatthe proposed algorithm outperforms several methods. In future the work can beexpanded by incorporating better restoration technique alongwith the efficient detection scheme with machine learning methods.

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