Development of an Improved Palm Vein Recognition System Using a Swarm Intelligent Based Support Vector Machine

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ABSTRACT

Several researches done in the area of palm vein biometric system ultimately aims for the improvement of the system performance. However, most of these works proved to have good efficiency rate but usually is compromised by a higher processing time. Therefore, in this study, a Particle Swarm Optimization technique is applied to optimize the parameter of Support Vector Machine to improve its performance and reduce it computational burden in palm vein recognition system. Experimental result shows that the proposed PSO-SVM technique outperformed the SVM technique in terms of recognition accuracy, sensitivity, specificity and false positive rate. Also, PSO-SVM technique is less computationally expensive than the SVM technique. Hence, palm vein recognition system based on PSO with SVM would produce a more reliable security system in access control.

Key words: Biometrics, Palm vein Recognition, Particle Swarm Optimization, Support Vector Machine

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1. BACKGROUND TO THE STUDY

Biometrics refers to the identification of humans by their characteristics or traits. It is the science and technology of measuring and analyzing biological data. Biometric identifiers are often categorized as physiological or behavioral characteristics; among the features measured akin to face, fingerprints, hand geometry, handwriting, palm vein, iris, retinal, and voice etc (Hong *et al.,* 2000; Raut and Humbe, 2014). The growing interest is due to the advantages offered by the biometric, as an optional tool for identification and authentication (Lee, 2015; Zhou and Kumar, 2011).

Hand vein recognition technology, a burgeoning biometrics mainly used for identification, has been proposed in recent years. Compared to fingerprint or other biological features, hand vein, including palm vein, finger vein and back vein, is much more reliable because it is highly distinctive and difficult to be changed by operation, as well as more feasible and easier for collecting data with non-contact acquisition system (Pan and Kang, 2011). These advantages make hand vein recognition technology more accurate and promising, which has attracted an increasing amount of attentions from research communities and industries all over the world (Li *et al.,* 2010).

The vein patterns are not easily spoofed, observed, damaged, obscured or changed. It is perceived as secure and integrated with "aliveness" detection. Palm vein authentication has a high level of authentication accuracy due to the uniqueness and complexity of vein patterns of the palm. The biometric data is based on human vein characteristics that stay constant throughout one's lifetime. As palms have more complex vascular patterns than fingers and provide more distinct features for pattern matching and authentication. Palm vein authentication has a high level of authentication accuracy due to the uniqueness and complexity of vein patterns of the palm (Raut and Humbe, 2014).

Several research done in the area of palm vein biometric system ultimately aims for the improvement of the system performance (Fischer *et al.,* 2012). However, most of these works proved to have good efficiency rate but usually is compromised by a higher processing time (Wu *et al.,* 2012; Noh *et al.,* 2016). This research tends to apply Particle swarm optimization (PSO) along with Support Vector Machines (SVM) for an improved palm vein recognition system.

2. LITERATURE REVIEW

2.1 Palm Vein Recognition

The human hand provides a rich set of biometric data that can be used in many ways, focusing on a particular hand region such as the fingertip, finger, palm, dorsal hand and 3D hand models or combining the features extracted from multiple regions into a multimodal biometric system. The most prominent approaches are: fingerprint, hand shape, palm print, palm vein and hand vein biometrics (palm vein, finger vein) (Hand-based biometrics, 2003).

Palm vein is a powerful biometric trait for human recognition. This is found that blood vascular net of each individual is unique. This palm veins are captured by the help of infrared light illumination. Unlike finger print and palm print, blood vessels lie below to skin therefore it is very difficult to forge the biometric system based on palm vein (Parihar and Jain, 2019). Palm vein technology works by identifying the vein patterns in an individual's palm. When a user's hand is held over a scanner, a near-infrared light maps the location of the veins. The red blood cells present in the veins absorb the rays and show up on the map as black lines, whereas the remaining hand structure shows up as white. This vein pattern is then verified against a preregistered pattern to authenticate the individual. As veins are internal in the body and have a wealth of differentiating features, attempts to forge an identity are extremely difficult, thereby enabling a high level of security (Sarkar *et al.*, 2010, Ahmed *et al.,* 2013).

2.2 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a computational search and optimization technique that have been empirically shown to achieve well on several optimization problems. It is extensively used to find the worldwide optimum explanation and solution in a complex search space (Kumar, Singh & Patro, 2016). PSO is a population-based optimization technique inspired by the behaviour of schools of fish, herds of animals or flocks of birds (Eberhart & Kennedy 1995). PSO is becoming one of the most important swarm intelligent paradigms for solving global optimization problems (Fuzhang, 2016). This algorithm has unfathomable intelligence background and is appropriate for scientific research and engineering application. Therefore, PSO algorithm has triggered the widespread attention of researchers in the field of evolutionary computation, and has attained a lot of research results over the years (Liu, 2016). Similarly, PSO is easy to implement and has been effectively functioned to resolve a varied collection of optimization problems.

Thus, because of its easiness and effectiveness in directing huge search spaces for optimal solutions and its dominance with respect to other Evolutionary algorithm techniques; PSO algorithm is engaged in this research to achieve an optimal parameter for SVM classification.

2.3 Support Vector Machine (SVM)

Support Vector Machines (SVM) are classification and regression methods which have been derived from statistical learning theory (Cervantes *et al.*, 2007). The concept is based on optimal linear separating hyperplane that is fitted to the training patterns of two classes within a multi-dimensional feature space. The optimization problem that has to be solved relies on structural risk minimization and is aiming at a maximization of the margins between the hyperplane and closest training samples. Support vector machine method classifies both linear as well as non-linear data. It transforms the data into higher dimension. The SVM finds hyperplane using support vectors and margin define by support vector. The data transform into dimension equals to the number of attribute in data. Hyperplane with maximum margin is classifying the data with high accuracy. There is high classification accuracy of support vector machine (Vapnik, 1995; Adetunji *et al.,* 2018).

The biggest difficulties in setting up the SVM model are choosing the kernel function and its parameter values. If the parameter values are not set properly, then the classification outcomes will be less than optimal (Morik *et al.,* 1999). In complex classification domains, some features may contain false correlations, which impede data processing. Moreover, some features may be redundant, since the information that they add is contained in other features. Redundant features can lengthen the computational time, influencing the classification accuracy. Hence, the classification process must be fast and accurate using the minimum number of features, which is a goal attainable through the use of feature selection. Feature selection has been applied to enhance classification performance, and to reduce data noise (Lee and Estivill-Castro, 2007; Geetha *et al*., 2009) If the SVM is adopted without feature selection, then the dimension of the input space is large and nonclean, lowering the performance of the SVM. Thus, the SVM requires an efficient and robust feature selection method that discards noisy, irrelevant and redundant data, while still retaining the discriminating power of the data. Features extracted from the original data are adopted as inputs to the classifiers in the SVM (Lin *et al.,* 2008; Adetunji *et al.,* 2018).

2.4 Related Works

Parihar and Jain (2019) presented a robust method to recognize palm vein using SIFT and SVM classifier. The proposed technique distinguishes between various people's palm vein. A powerful SIFT method was used to uniquely identify palm veins. This was done because of translation, rotation and scale invariance properties of SIFT technique. Thereafter, the SVM classifier was used to correctly identify the palm veins. The experimental results show a good precision and recall. Recognition accuracy of 92.50% and 88.75% for left and right hand respectively.

Sehgal (2015) proposed an efficient palm recognition using LBP and SVM. The proposed system was implemented using MATLAB and LBP method and uses SVM technique which reduces the complexity there by a increase the performance. The system has an average 97.5% recognition rate. This Research attempted to reduced complexity for Palm vein recognition. Palm vein recognition is easily implemented using a feature extraction algorithm (LBP) and SVM for classification which reduces complexity thereby increases performance. The performance analysis is done using CASIA database.

Qin *et.al.* (2013) proposed other methods, one is finger vein pattern figure extraction and positioning features information. Furthermore, a region-based matching pattern analyzed by the SIFT matching method. Finally, the finger-vein shape/pattern and SIFT features are merged. Feature extraction into three-part finger-vein shape, SIFT feature point and finger-vein orientation then make sub-region partition, matching score combination for decision. This paper shows 90% GAR value at the less value of FAR. This paper is based on shape and orientation so the appropriate image ROI is required to get efficient score matching.

Connie *et al.* (2005) presented an automated palm print recognition system. The system automatically captures and aligns the palm print images for further processing. Several linear subspace projection techniques were tested and compared. Specifically, principal component analysis (PCA), fisher discriminant analysis (FDA) and independent component analysis (ICA) were used. In order to analyze the palm print images in multi-resolution-multi-frequency representation, wavelet transformation was adopted. The images were decomposed into different frequency sub bands and the best performing sub band was selected for further processing. Experimental result shows that application of FDA on wavelet sub band was able to yield both FAR and FRR as low as 1.356 and 1.492% using the palm print database.

3. METHODOLOGY

This work developed a method to extract features from the sub-images of palm vein which can be used for personal identification and verification. Histogram equalization and Gabor filter algorithm were used at pre-processing and feature extraction levels respectively. Support Vector Machine optimised by particle swarm optimization was used for classification. The parameters used to measure and evaluate the overall performance of the developed system are recognition accuracy, recognition time, sensitivity, specificity and false rejection rate. The required stages involved in developing palm vein recognition system are highlighted as follows:
Stage 1: Palm vein Acquisition
Stage 2: Location of Region of Interest (ROI)
Stage 3: Palm vein Pre-processing
Stage 4: Texture Feature Extraction Based on Gabor Filter
Stage 5: Training and Classification
Stage 6: Recognition/Testing

3.1 Image acquisition

Palm vein pattern is not easily seen in visible light and thus cannot be captured by ordinary camera. Therefore, near infrared CCD (Charge-coupled device) sensitive camera were used to capture forty (120) individuals' palm vein. During the image acquisition process, the users were required to stretch their palm straight on the platform of the scanner. The images were acquired in 256RGB colours (8 bits per channel) format, with resolution of 640 x 480 pixels and 260 x 300 pixels for palm vein. The three colour components are important in the pre-processing stage as it can distinguish the background, rings and shadow from the hand image. The colour distinction helped to trace the hand more accurately and reliably. For each individual, five palm vein images were captured (120*5 equals 600 images). Figure 3.1 shows the captured palm vein samples stored in a database. Three hundred (300) palm vein images were used for training the system while three hundred (300) images were used to test the system and finally saved into the database in jpeg format.

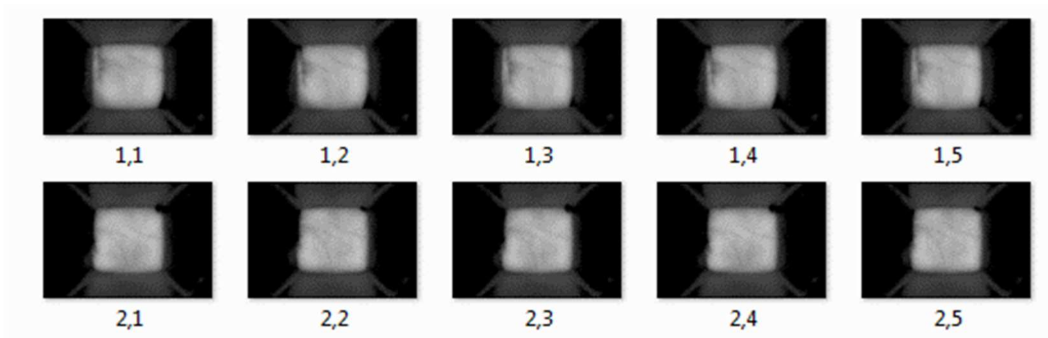

Figure 3.1: Captured palm vein images

3.2 Location of the Region of Interest (ROI)

After image capturing, a small area (71*71 pixels) of the palm vein image was located as the Region of Interest (ROI) to extract the features and to compare different palms. Using the features within ROI for recognition improved the computational efficiency significantly. Further, because this ROI normalized coordinate based on the palm boundaries, the recognition error caused by users who slightly rotate or shift his/her hand was minimized. The following steps were followed to extract the ROI for palm vein:

1) Image binarization;
2) Obtain the boundaries of the gaps;
3) Compute the tangent of the two gaps use this tangent (The line connects (x1, y1) and (x2, y2)) as the Y-axis of the palm coordinate;
4) Use a line passing through the midpoint of the two points (x1, y1) and (x2, y2), which is also perpendicular to the Y-axis, as the X line perpendicular to the tangent computed in 3;
5) The ROI was located as a square of fixed size whose centre has a fixed distance to the palm co-ordinate origin;
6) Extract the sub image within the ROI.

3.3 Palm vein Pre-processing

Before feature extraction, it is necessary to ensure noise reduction, contrast enhancement and elimination of the variations caused by rotation and translation. The technique that was used for both fingerprint and palm vein enhancement is histogram equalization. Histogram enhances the global contrast of an image. The original and the pre-processed images of palm vein are shown in Figure 3.2.

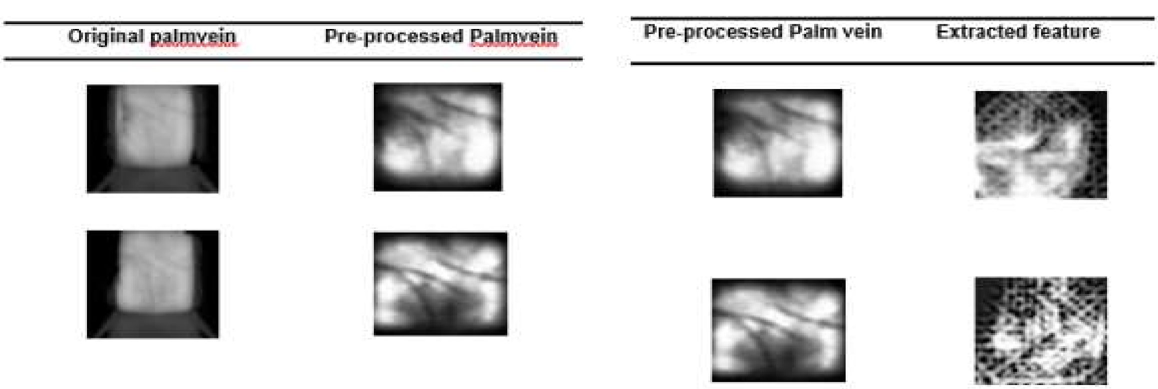

Figure 3.2: Original and pre-processed images, and Extracted features of palm vein

3.4 Palm Vein Feature Extraction based on Gabor Filter Algorithm

This is the process of using the most important information of the cropped palm vein images for classification purpose. The feature extraction was carried out using Gabor filter as represented by equation 3.1. Gabor filter is a band pass filter which has orientation- selective and frequency-selective features. Samples of pre-processed and extracted features are shown in Figure 3.2. A two-dimensional Gabor filter is a combined function with two components: a complex plane wave and a Gaussian-shaped function. It is defined as following:

$$G(x,y) = k \exp\left\{-\frac{1}{2}\left(\frac{x_0^2}{\sigma_x^2} + \frac{y_0^2}{\sigma_y^2}\right) + j2\pi f_0 x_0\right. \quad (3.1)$$

$$x_0 = xcos\emptyset + ysin\emptyset \quad (3.2)$$

$$y_0 = -xsin\theta + ycos\theta \quad (3.3)$$

Where k = $1/_{(2\pi\sigma_x\sigma_y)}$, $j = \sqrt{-1}$, θ is the orientation of Gabor filter. f_0 represents the filter centre frequency, σ_x and σ_y are the scales of the Gaussian shape, x_0 and y_0 are the two vertical Gaussian axes.

3.5 The PSO for Parameter optimization

During the training and testing phase, the features extracted by Gabor filter was presented to the PSO model. The learning and testing process is described step-by-step as follows.

1. Set parameter ω_{min}, ω_{max}, c_1 and c_2 of PSO
2. Initialize population of particles having positions x_j and velocities v_j
3. Set iteration k = 1
4. Calculate fitness of particles $F_{ij}(t) = f(\vec{x}_{ij}(t))$ and find the index of the best particle b
5. Select $Pbest_{ij}(t) = \vec{x}_{ij}(t)$ and $Gbest_j(t) = x_{bj}(t)$
6. $\omega = \omega_{max} - k \times (\omega_{max} - \omega_{min})/Max\_no$
7. Update velocity and position of particles

$$\vec{v}_{ij}(t+1) = \omega\vec{v}_{ij}(t) + c_1 r_1\left(P_b - \vec{x}_{ij}(t)\right) + c_2 r_2\left(G_b - \vec{x}_{ij}(t)\right)$$

$$\vec{x}_{ij}(t+1) = \vec{x}_{ij}(t) + \vec{v}_{ij}(t+1)$$

8. Evaluate fitness $F_{ij}(t+1) = f(\vec{x}_{ij}(t+1))$ and find the index of the best particle b_1
9. Update $Pbest$ of population
   If $F_{ij}(t+1) < F_{ij}(t)$ then $Pbest_{ij}(t+1) = \vec{x}_{ij}(t+1)$ else
   $Pbest_{ij}(t+1) = Pbest_{ij}(t)$
10. Update $Gbest$ of population
   If $F_{bj}(t+1) < F_{bj}(t)$ then $Gbest_j(t+1) = Pbest_{bj}(t+1)$ and set $b = b_1$ else
   $Gbest_{bj}(t+1) = Gbest_j(t)$
11. If $k < Max\_no$ then $k = k + 1$ and goto step 6 else goto step 12
12. Output optimum solution as $Gbest_j(t)$.

3.6 Classification Using SVM

The Selected best global position P_i of the particle swarm trained the SVM with the detected feature subset mapped by P_i and modelled with the optimized parameters C and σ using equation (3.4):

$$min \quad \frac{1}{2}||P_i||^2 + C\sum_{i=1}^{N}\xi_i \qquad (3.4)$$

$$\text{Such that} \quad \sum_{i=1}^{N} P_i x_i \geq \left(\frac{1-\xi_i}{y_i}\right) - b \qquad (3.5)$$

$$i = 1, 2, \ldots, N, \qquad \xi_i \geq 0, \qquad i = 1, 2, \ldots, N,$$

Where N is the size of the training dataset and C is a positive regularization constant or cost function, which defines the trade-off between a large margin and a misclassification error. P_i. The following rule was applied to obtain the final classification of each instance:

$$y_i = \arg\max_{\mathrm{k}(1...\mathrm{k})}(P_i^T y_i(x_i) + b_i) \qquad (3.6)$$

Each class was labelled base on classification.

3.7 Performance Measures of the Developed System

The performance of trained and recognized subjects was measured against recognition accuracy, recognition time, sensitivity, specificity and false positive rate.

The following parameters were used to measure and evaluate the overall performance of the developed system:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad (3.7)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \qquad (3.8)$$

$$\text{False Positive Rate} = \frac{\text{FP}}{\text{TN} + \text{FP}} \qquad (3.9)$$

$$\text{Recognition Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \qquad (3.10)$$

3.8 Implementation

MATLAB R2018 on Windows 10 64-bit operating system, Intel®Core™ i5-2540M CPU@2.60GHz Central Processing Unit, 6GB Random Access Memory and 500GB hard disk drive was used to implement the proposed work. Testing and recognition of the proposed system were performed using two training images per individual, five untrained subjects were used as imposters. The flow diagram of the proposed system is shown in Figure 3.3. Total number of 300 images were used to test the proposed system.

4. RESULTS AND DISCUSSION

The results obtained from PSO-SVM technique and SVM based on the aforementioned metrics is presented in Table 4.1. SVM technique was considered to test for the effect of optimizing SVM using PSO. The result was obtained by experimenting each technique using varying threshold values; 0.21, 0.35, 0.46 and 0.75 with respect to the performance metrics.

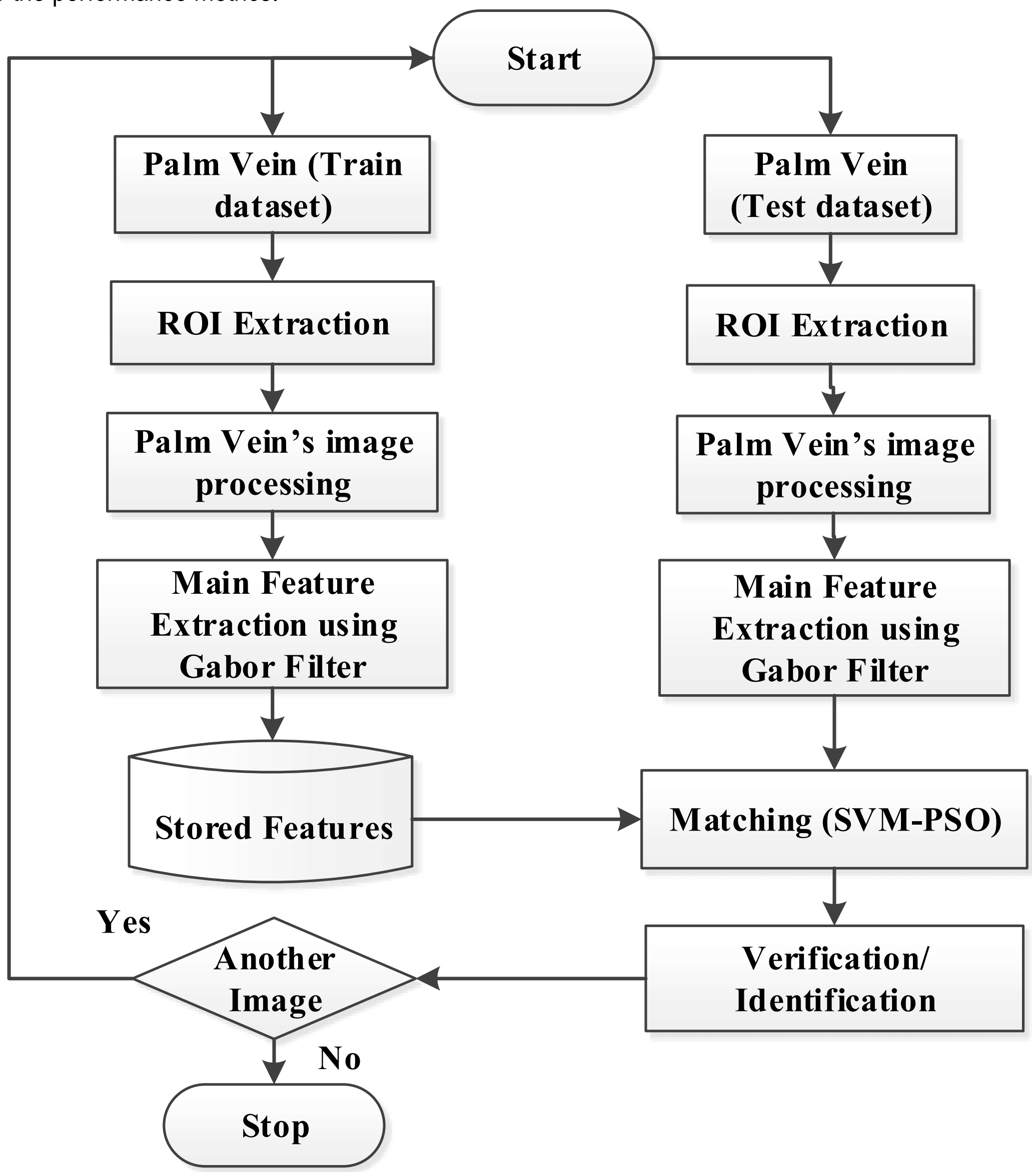

Figure 3.3: A flow diagram of Testing Stage of the proposed system

Table 4:1: Result of the Proposed Technique

Threshold Value	Method	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Recognition Time (Sec)
0.21	**PSO-SVM**	11.00	98.50	89.00	95.33	171.68
	SVM	14.00	97.00	86.00	93.33	178.32
0.35	**PSO-SVM**	8.00	98.00	92.00	96.00	169.73
	SVM	11.00	96.50	89.00	94.00	178.52
0.46	**PSO-SVM**	5.00	97.50	95.00	96.67	168.98
	SVM	8.00	96.00	92.00	94.67	179.64
0.75	**PSO-SVM**	**3.00**	**97.00**	**97.00**	**97.00**	**163.12**
	SVM	**6.00**	**95.50**	**94.00**	**95.00**	**177.56**

The result obtainable from Table 4.1 reveals that there is significant variation in the result based on the increase in threshold value. However, the best performance was achieved at threshold value of 0.75. The table reveals that at threshold value of 0.75 the PSO-SVM achieved a false positive rate of 3.0%, sensitivity of 97.00%, specificity of 97.0% and accuracy of 97.0% at 163.12 seconds. Also, at threshold value of 0.75 the SVM achieved a false positive rate of 6.0%, sensitivity of 95.50%, specificity of 94.0% and accuracy of 95.0% at 177.56 seconds. It can be inferred from the results based on the performance metrics that the PSO-SVM model gave an increased 2.0% recognition accuracy, 1.5% sensitivity, 3.0% specificity and a decreased FPR of 3.0% over the SVM model. The outcome of this research reveals that the PSO-SVM outperformed the SVM model in palm vein recognition.

Figure 4.1 shows the graph of recognition time against the threshold value. Zhou *et al.* 2008 stated that PSO will achieve faster convergence speed and better precision when applied to optimize the parameters of SVM. Also, the novel approach suggested by Manekar and Waghmare (2014) stated that the accuracy of SVM can be improved by the application of hybrid cultural algorithm with PSO. The results presented in this study also establishes the fact that the application of PSO achieved a faster convergence speed, better sensitivity and slightly improve the accuracy of SVM.

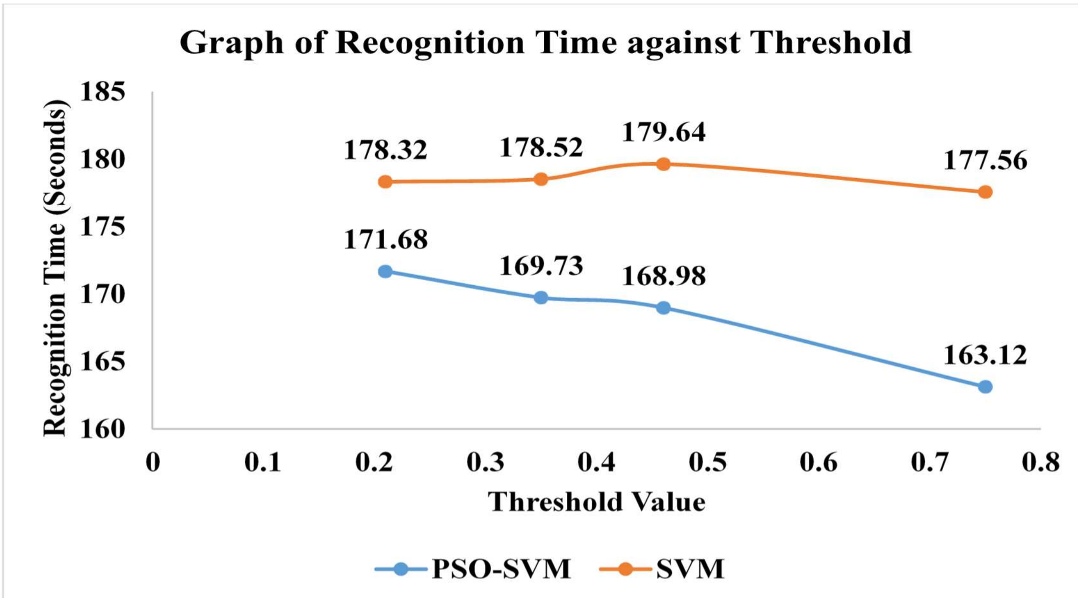

Figure 4.1: Graph of Recognition Time against Threshold

The paired t-test analysis conducted between the recognition time of PSO-SVM and SVM technique reveals that there is significant distinction in the test result; having a mean difference ($\mu = -10.13$). Nevertheless, the result confirmed that the PSO-SVM technique is statistically significant at $P < 0.01; P = 0.009$ with $t\ value = -6.126$. Test of significance of the recognition time evaluated at 95% confidence level shows that there was significant difference between the PSO-SVM and SVM technique. The t-test result validates the fact that the PSO-SVM technique is less computationally expensive compared to SVM technique

5. CONCLUSION AND RECOMMENDATION

In view of the results, the technique i.e. PSO-SVM is more accurate, sensitive, specific and less computationally expensive compared to SVM model. Therefore, application of PSO along with SVM will give an improved accuracy, sensitivity, specificity and false positive rate. Furthermore, it will also help to reduce the computational burden associated with SVM when being applied to problem with large dimension. It is clearly evident that PSO-SVM method is well matched to the other conventional palm vein recognition methods based on its performance. Hence, palm vein recognition system based on PSO with SVM would produce a more reliable security system for access control. It will also help in maintaining high recognition accuracy in palm vein recognition systems as well as computational efficiency in building a truly robust system.

REFERENCES

1. Adetunji, A. B., Oguntoye, J. P., Fenwa, O. D., & Omidiora, E. O. (2018). Reducing the Computational Cost of SVM in Face Recognition Application Using Hybrid Cultural Algorithm. IOSR Journal of Computer Engineering (IOSRJCE). 20(2): 76-85.
2. Ahmed, M. A., Ebied, H. M., El-Sayed, M., & Abdel-badeeh, M. S. (2013). Analysis of palm vein pattern recognition algorithms and systems. International Journal of Bio-Medical Informatics and e-Health. 10-14.
3. Biometrics, H. B. (2003). Biometric Technol. Today, 11(7), 9-11.
4. Cervantes, J., Li, X., & Yu, W. (2007). SVM classification for large data sets by considering models of classes distribution. In 2007 Sixth Mexican International Conference on Artificial Intelligence, Special Session (MICAI) (pp. 51-60).
5. Connie, T., Jin, A. T. B., Ong, M. G. K., & Ling, D. N. C. (2005). An automated palmprint recognition system. Image and Vision computing, 23(5), 501-515.
6. Eberhart R. C, Kennedy J. (1995). A New Optimizer Using Particle Swarm Theory. In Proceedings of the 6th International Symposium on Micro-machine Human Science. 39–43.
7. Fischer, M., Rybnicek, M. and Tjoa, S. (2012). A novel palm vein recognition approach based on enhanced local Gabor binary patterns histogram sequence. International Conference on Systems, Signals and Image Processing, pp.429–432.
8. Fuzhang Z. (2016). Optimized Algorithm for Particle Swarm Optimization. World Academy of Science, Engineering and Technology International Journal of Physical and Mathematical Sciences, 3(3): 1-6.
9. Geetha, A., Ramalingam, V., Palanivel, S., & Palaniappan, B. (2009). Facial expression recognition–A real time approach. Expert Systems with Applications, 36(1), 303-308.
10. Hong, L., Jain, A. and Pankanti, S. (2000), Biometric Identification, Communications of the ACM. 43(2), 91-98.
11. Kumar A., Singh B. K. & Patro B. D. K. (2016). "Particle Swarm Optimization: A Study of Variants and Their Applications." International Journal of Computer Applications, 135(5): 24-30.
12. Lee, K., & Estivill-Castro, V. (2007). Feature extraction and gating techniques for ultrasonic shaft signal classification. Applied Soft Computing, 7(1), 156-165.
13. Li, Q., Zeng, Y., Peng, X., Yan, K. (2010): Curvelet-based palm vein biometric recognition. Chin. Opt. Lett. 8(6), 577–579.
14. Lin, S. W., Lee, Z. J., Chen, S. C., & Tseng, T. Y. (2008). Parameter determination of support vector machine and feature selection using simulated annealing approach. Applied soft computing, 8(4), 1505-1512.
15. Liu Yi. (2016). Study on an Improved PSO Algorithm and its Application for Solving Function Problem. International Journal of Smart Home 10 (3): 51-62.
16. Manekar and Waghmare (2014). Improving Accuracy of SVM Using Hybrid Cultural Algorithm. International Journal Computer Technology & Applications (IJCTA), 5(3), pp1194-1197
17. Morik, K., Brockhausen, P., & Joachims, T. (1999). Combining statistical learning with a knowledge-based approach: a case study in intensive care monitoring. Proc. 16th International Conf. on Machine Learning, Morgan Kaufmann, San Francisco, CA, 1999, 268–277.
18. Noh, Z. M., Ramli, A. R., Saripan, M. I., & Hanafi, M. (2016). Overview and challenges of palm vein biometric system. International Journal of Biometrics, 8(1), 2-18.
19. Ola B. O., Awodoye O. O. and Oguntoye J. P. (2019). A comparative study of particle swarm optimization and gravitational search algorithm in poultry house temperature control system. World Journal of Engineering Research and Technology. 5(6): 272-289.

20. Pan, M., & Kang, W. (2011). Palm vein recognition based on three local invariant feature extraction algorithms. In Chinese Conference on Biometric Recognition (pp. 116-124). Springer, Berlin, Heidelberg.
21. Parihar, R. S., & Jain, S. (2019). A Robust Method to Recognize Palm Vein Using SIFT and SVM Classifier. International Conference on Sustainable Computing in Science, Technology & Management. 1703-1710.
22. Qin, H., Qin, L., Xue, L., He, X., Yu, C., & Liang, X. (2013). Finger-vein verification based on multi-features fusion. Sensors, 13(11), 15048-15067.
23. Raut, S. D., & Humbe, V. T. (2014). Review of biometrics: palm vein recognition system. IBMRD's Journal of Management & Research, 3(1), 217-223.
24. Sarkar, I., Alisherov, F., Kim, T. H., & Bhattacharyya, D. (2010). Palm vein authentication system: a review. International Journal of Control and Automation, 3(1):27-34.
25. Sehgal, P. (2015). Palm recognition using LBP and SVM. Int. J. Inf. Technol. Syst, 4(1), 35-41.
26. Vapnik, V. (1995). The nature of statistical learning theory. (Springer-Verlag, New York, 1995).
27. Wu, W., Yuan, W-Q., Guo, J-Y., Lin, S. and Jing, L-T. (2012). Contact-less palm vein recognition based on wavelet decomposition and partial least square. Biometric Recognition Springer, Berlin, Heidelberg. pp.176–183.
28. Zhou, J., Bai T., Tian J. and Zhang A. (2008). The study of SVM optimized by Cultural Particle Swarm Optimization on Predicting Financial Distress. IEEE conference 2008.