International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-9 Issue-2, July 2020

A Comparative Performance Analysis of Multimodal-Multialgorithm System Framework Based on Rank Level Fusion

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Abstract: The Unimodal biometric framework have various fundamental issues, for example, intra-class alteration, noisy data, failure-to-enroll, spoofing attacks, unacceptable error rate and non-universality. To defeat this shortcoming multibiometric is a decent alternative where we can utilize at least two individual modalities. This paper gives a comparative analysis of multi-algorithm and multimodal system framework based on rank level fusion. An effective combination strategy that integrates information given by different domain specialist dependent on rank level fusion approach is utilized to enhance the presentation of the framework. The rank of individual matcher is combined using the highest rank, Borda count, weighted Borda count, nonlinear weighted approach and Bucklin combination approach. The outcomes of the results show there is a noteworthy exhibition enhancement in the identification accuracy can be accomplished when contrasted those from unimodal frameworks. The outcomes also reveal that combination of individual modalities can enhance the biometric system performance. The experiment based on multimodal (NIST BSSR1 multimodal database of fingerprint and face) and multialgorithm (Hong Kong Polytechnic University database of palmprint) system shows an improvement in term of the Rank-1 identification rate of the system.

Keywords : Unimodal; Multibiometric; Rank level fusion; Highest rank; Borda count; Weighted Borda count; Nonlinear weighted; Bucklin; Multi-algorithm; Multimodal;Rank-1 identification.

I. INTRODUCTION

The Biometric is based on pattern recognition based system which is able to recognize the person by its own physiological (fingerprint, face, iris, ear) and behavioral (signature, voice, eye movement, mouse dynamic) traits. Depending on the requirement of the system, biometric can work either in verification mode or identification mode. The verification mode consists of the verification of user identity by correlating the stored claimed user biometric traits with his own biometric traits which is already captured in the database. The identification mode enabled system can recognize the claimed user by searching for a match of his own biometric traits with others stored in the template [1]. This paper deals with the comparative analysis of multi-algorithm and multimodal based system dependent on rank level fusion. In ongoing year the utilization of biometric based framework for authentication purpose gradually increases, an example of such application included airport security, border security, access to buildings, computer system and ATM.Biometric based framework is highly protected than the traditional based system ,which depends on a password (security based on knowledge) and token-based security. The main drawback with knowledge and token based security is that the password can be easily guessed, misplace or it can be forgotten and any third party can easily access the system. To overcome these difficulties biometric can be used to authenticate the users by his own biometric traits which are never stolen and very difficult to guess [2]. Unimodal framework which is depends on a single modality like Fingerprint, face, iris and ear have several inherent problems like noisy data (existence of dirt in sensor) , intra-class variation, unsatisfactory error rate, deficiency-to-enrollment and spoof attacks. Multibiometric system address this issue and defeated some of these shortcoming by combining evidence receive from various sources ,these include multi-sensor (combining evidence from multiple sensors of the same biometric traits) , multi-instance (evidence from different finger of a person) , multimodal (evidence from more than one biometric traits like face and iris) and multi-algorithm (evidence from multiple feature extraction algorithm like PCA and LDA for face) [3] .Multibiometric depends on combination approach ,where the feature sets from multiple evidence is combined together in a proper manner to reduced the deficiency of unimodal system. Information fusion can be referred as the problem which is faced when the multiple source are combined together [4]. The primary purpose for the accomplishment of multibiometric framework is its combination methodology, means using proper fusion strategy, we can upgrade the system performance in terms of accuracy, error rate and acceptance rate. The general combination strategy can be sorted into five distinct levels of fusion, these are sensor level (combined raw data from different sensors), feature level (features of various biometrics traits are combined), score level (combining the score of genuine and imposter), decision level (consolidating the decision created by set of classifiers) and rank level (consolidate the rank gain by individual matcher). Biometric system that uses early stage fusion (sensor and feature) approach are found highly adequate than post stage fusion (score, decision and rank) methods. Sensor level fusion handles the issue of noisy data (existence of dirt on the sensor), but the other problem of unimodal system is remaining same. On account of face recognition systems, the performance of the system may be degraded by variation in terms of pose, illumination and expression. Furthermore the behaviour of the voice based unimodal system is also influenced by noisy environment.

Revised Manuscript Received on June 22, 2020.
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In this situation multibiometric is a good option to overcome the limitation faced by individual modality which can improve the performance and give better classification accuracy [5] .So as to improve the confirmation execution and overcome the drawbacks of the unimodal biometric system, researchers have recommended the information fusion in biometric. Fusion process in biometric may be performed at different levels, such as sensor level, feature level, score level, decision level and rank level [6].Among all the combination technique matching score level fusion is considered more attractive and easy to implement due to accessing conformability and scores combining ability [7].

Biometrics features contain more valuable information than match score and for this reason feature level fusion provide better recognition capabilities than the rest fusion methods, yet, it is hard to accomplish practically speaking because of the obscure relationship of various element spaces of biometric frameworks, because of the huge dimensionality of features. Decision level fusion is too rigid to implement due to a limited number of information at this level. Among all the combination techniques score level combination is exceptionally well known and easy to actualize; so many works has been accomplished in the domain of score level fusion. Researcher liked to utilize score level combination because of simplicity of consolidating matching score. Because of heterogeneous natures of matching score produced by various biometric modalities, a technique known as normalization is mandatory, which convert these scores into a typical range before combination happens [8, 9].

Score level combination method can be classification as: a) transformation-based score fusion (match score initially convert into a common domain and then join) like sum rule, weighted sum rule and product rule. b) classifier based (score from various matcher are utilized to prepare a classifier) like a support vector machine (svm) and c) density based fusion like likelihood ratio test [10].In transformation-based score combination, preceding combination, the normalization of matching scores into a typical area and range is required as a result of contradiction of few biometric attributes. In classification-based score level combination the output scores from various biometric modalities are considered as a feature vector and each matching score are treated as an part of feature vector. Density-based score combination considers an explicit assessment of score densities of genuine and imposter type that causes expanding usage unpredictability. Evolutionary approaches assumes a significant job in multibiometric, it create an ideal solution among a large community and finally achieve the optimum solution through the refreshing the previous history of the particle [6] .Combination dependent on rank level combination is moderately new and understudied issue, which has high potential for appropriate solidification of the different unimodal biometric matcher output[11]. The rank level combination is accomplished by sorting the possible matches provide by each biometric matcher in a decreasing order of confidence [12]. In an identification based biometric system, the biometric traits (fingerprint image) of a claimed users is compared to the fingerprint database (gallery database) consist of biometric data and therefore set of similarity scores are produced which are organize in diminishing request and dependent on this requesting a set of whole number or ranks is allotted to these retrieved identities. The best match is decided by the lowest rank and the genuine identity is the true identity of the probe that corresponds to that match, else it is treated as imposter one. Within the sight of low quality biometric information the recognizable proof precision of the framework might be diminished and because of that the closeness between the test and comparing exhibition picture likewise decreased. To enhance the accuracy of identification, multibiometric combination is a decent decision where a few confirmations are united by various biometric sources [13].

The efficiency level of multibiometric framework is estimated by the false acceptance rate (FAR) and false rejection rate (FRR). FAR is the likelihood of a fraud being acknowledged as a real user, though FRR is the likelihood of a certifiable client being dismissed as a faker user [14]. At the point when the two element vectors relating to a similar individual are thought about we get a score known as genuine score, while two element vectors relating to two distinct people are looked at we get imposter score. The value of FAR is the proportion of number of erroneously acknowledged faker score and total number of fraud scores, GAR (certifiable acknowledged rate) is the proportion of the accurately acknowledged authentic score and the total number of genuine scores. These two parameters are united in a curve known as receiver operating characteristic (ROC) [12].

$$FAR=\frac{\textit{imposter scores exceding threshold}}{\textit{total imposter scores}} \quad (1)$$

$$GAR=\frac{\textit{geniune scores below threshold}}{\textit{total geniune scores}} \quad (2)$$

FRR and FAR are complement of each other, implies little variation in FRR prompts a bigger value of FAR and a littler FAR as a rule infers a bigger FRR, both the parameter FAR and FRR are utilized to measure the exhibition of the framework. A zero value of FAR signifies that no imposter is acknowledged as an authentic individual.GAR is additionally utilized to estimate the level of system accuracy, which is estimated as the fraction of genuine score surpassing the predefined threshold value [9]. The rest of this paper is sorted out as follows: Section 2 highlights the details of related works dependent on rank level fusion, segment 3 gives experiences about rank level combination, area 4 gives insights regarding the test results dependent on multimodal and multi-algorithm framework, segment 5 discuss about the comparative outcomes and section 6 concludes the papers.

II. RELATED WORKS

Multimodal based biometric systems combine the outcomes receive from different sources of biometric modalities for the identification purpose. These distinctive biometric features can emerge from different modalities like fingerprint, face and iris. In this segment it is discuss about the related research dependent on multimodal biometrics. In 2007, Noore et al. [15] presented a wavelet change based picture combination calculation that creates a connect picture by utilizing pictures of multi-modular biometric. This algorithm first converts the biometric image into wavelet domain and produces a fused image by consolidate the co-efficient of wavelet.

The concatenate image is then mixed utilizing a private key which is originated from Fibonacci transforms. In 2008, Wang et al. [16] proposed a multi-modal person identification framework dependent on sensor level fusion utilizing palm print and palm vein as biometric modalities. These images are melded utilizing contrast upgrading combination rule in which multi scale edge of the palmprint and palm vein pictures are solidified. Locality preserving projections (LPP) technique is utilized to select the Laplacian palm feature from the fuse images. The analysis result shows that the Laplacian palm approach gives a superior representation and lower error rate in palm acknowledgment. In 2009, Kisku et al. [17] proposed a sensor level combination based multi-modular individual personality confirmation framework utilizing face and palmprint. Feature extraction is practiced utilizing the scale invariant element change (SIFT) administrator and acknowledgment is performed utilizing recursive plunge tree traversal approach comprise of movable basic chart coordinating between a couple of melded pictures via looking through relating focuses. The test outcome shows the profitability of the proposed system with 98.19% accuracy which beats various procedures when it is differentiated and the unimodal palmprint based structure. Kumar et al. [18] played out a hand based individual ID framework by incorporating palmprint and hand-geometry highlights. The principle preferred position of the proposed framework is that clients don't encounter the trouble of using two special sensors. Highlight link approach is utilized to combine the element of palmprint and hand-geometry.FAR of 5.08% and FRR of 2.25% are acquired utilizing highlight level combination. Feng et al. [19] introduced a novel combination technique for individual recognizable proof utilizing face and palmprint. Experimental results show that ICA (Independent component analysis) based feature level fusion achieved 99.17% of recognition accuracy which outperform than PCA (Principal component analysis) with 95.83%.

Valentine et al. [20] proposed a weighted sum rule score level fusion based multimodal system using face and iris, based on ORL face and CASIA iris database the Recognition accuracy of 98.75% is achieved. Kumar and kumar [21] proposed a weighted sum rule score level fusion based multimodal framework using palmprint and iris, proposed Aco based achieved EER of 0.0011 using sum rule, and EER=0.004 using product rule. Liang et al. [22] introduced a multimodal framework using fingerprint and face based on OPT (order preserving tree), NIST multimodal (face, fingerprint).It achieved a GAR of 99.8% using OPT. Yu et al. [23] proposed a palmprint, fingerprint and hand-geometry based system using AND, OR and Majority voting, 0.15% Recognition rate achieved using majority voting, 1.68% using AND rule and 0.64% using OR rule. Kumar et al. [24] introduce an evolutionary technique based decision level fusion scheme for multimodal system using palmprint and hand vein biometrics, Ant Colony Optimization (ACO) is utilized to find the fusion parameters by choosing them dynamically.

Monwar et al. [9] proposed a rank level fusion based multimodal framework using face, ear and signature. The feature extraction algorithms like principle component analysis (PCA) and Fisher's linear discriminant analysis technique are utilized for independent matchers of face, ear and signature. The ranks of every independent matcher are united together using the highest rank, Borda count and logistic regression technique. The trial results show that the exhibition of the framework can be improved even within the sight of the low nature of information.

In the same year, Abaza and Ross [25] introduced a multimodal framework using quality based rank level fusion. In this study, they suggested few basic yet incredible adjustments to improve the exhibition of the rank level based framework within the sight of feeble classifier and low nature of information. The experiment carried out with two or three hundred clients and uncover that the recommended alteration to the most elevated position and Borda check can upgrade the rank-1 precision. Kumar and Shekhar [26] developed a multiple palmprint representation based on rank level fusion. In this paper they explore a few combination systems like Borda count, Weighted Borda count, highest rank method, logistic regression and Bucklin method. The exploratory outcome shows that utilizing different portrayal of palmprint, the improvement in the acknowledgment exactness can be accomplished when contrasted with those from individual palmprint portrayal. Marasco et al. [13] invent the issue of change in rank authorized to the certified personality in multimodal framework when the nature of information is low. The exhibition is done on the face and Ocular Challenge Series (FOCS), made out of three frontal appearances for every subjects for 407 subjects. The exploratory outcome shows that changes in the highest rank fusion scheme perform superior than the other non-learning based rank level fusion method. Monwar and Gavrilova [27] developed a multimodal framework using rank level fusion based on Markov chain technique for face, iris and ear. In this work, for face and ear recognition fisher image technique is utilized and for iris recognition Hough transform technique is utilized. The test result shows the prevalence of the proposed approach analyzed over other rank level based methodology.

Sharma et al. [28] proposed a refinement in existing rank level combination approach utilizing two levels of hierarchy. The proposed work consists of serial and parallel combination which combines the outcome of different rank level fusion approach and widely assessed on multi-algorithm, multi-instance and multimodal biometric system forms by a combination of three available datasets:

- NIST BSSR1 (www.itl.nist.gov/iad/894.03/biometricscores) score database of multimodal biometrics.
- Face Recognition Grand Challenge V2.0 [29].
- LG4000 (http://biometrics.idealtest.org/) iris images.

The test result shows that the proposed techniques outflank other aggressive rank combination strategy in rank one acknowledgment rate.

Borade et al. [30] introduced a face acknowledgment utilizing PCA and LDA dependent on the Borda count approach. The experiment results show that combination of PCA and LDA utilizing a Borda count approach has improved acknowledgment over individual one. The acknowledgment pace of 95% has accomplished by the combination of PCA and LDA at rank level combination utilizing Borda tally approach.

III. RANK LEVEL FUSION

Rank level combination can be utilized to consolidate the biometric matching scores from the diverse biometric modalities including face, fingerprint, palmprint and iris. This combination can be utilized for execution upgrade in the unimodal biometric framework by joining numerous classifier yields that utilizes various classifiers like Support vector machine (SVM), neural system, and decision tree. Any biometric acknowledgment framework can have the option to producing matching scores for the input user with those of the enlisted potential identities. The diverse arrangement of all conceivable client ranks can be positioned by arranging the matching scores in the dropping request. A biometric framework can distinguish an obscure client by creating ranks which is a whole number allotted to every client personality. Rank level combination is an approach where different ranks from the distinctive biometric matcher are consolidated together to shape a single rank which further used to build up the identity of a person with higher certainty. The matching score accommodate more data than rank and hence match score level combination is more well known and adaptable than rank level combination. Be that as it may, the rank level combination scheme doesn't require conversion of ranks into a uniform discipline and are easy to implement [31].

3.1 Ranks combining schemes: Assume N is the users enrolled in the database and the total number of classifiers is C. consider $r_{i,j}$ be the rank generated by the i^{th} classifier for the user j in the database, where $i = 1 \dots . C$ and $j = 1 \dots . N$, and after implement rank level fusion R_j be the final rank for the user j .

- Highest Rank Fusion : In this approach, the fused rank of a user is calculated as the least rank achieved by the various classifiers, in mathematically it very well may be communicated as follows:

$$\mathrm{R_j} = \min_{i=1} r_{i,j} \qquad (1)$$

According to [32] the ties between the users can be broken randomly and to solve such ties we can modify the fusion rule by introducing a small perturbation factor, €, in equation (1):

$$\mathrm{R_j} = \min_{i=1} r_{i,j} + \epsilon_j \qquad (2)$$

Where $$\epsilon_j = \frac{\sum_{i=1}^{C} r_{i,j}}{K} \qquad (3)$$

The possibility of occurrence of such ties will be less if the numbers of enrolled user identities are huge and the numbers of matcher utilized in the combination process are small. One of the main advantages of this fusion scheme lies in the usage of the each biometric matcher strength. However, occurrences of more ties may be possible due to the large number of matcher which is the significant downside with this technique. Therefore, this technique is best suitable for biometric system having a large number of users with a small number of matchers.

- Borda Count Method : This technique consist of by applying the sum of individual matcher rank to get a fused rank:

$$R_j = \sum_{i=1}^{C} r_{i,j} \qquad (4)$$

The main advantages of the Borda count approach compared to the highest rank is that it has the potential to account for the ranks variability because of the large classifiers. This approach considered statistically independently, i.e., ranks generated for a given individual by various matchers are independent in nature and that all of them achieve well [4].This is one of the significant disadvantage of the Borda count technique, where combination is somehow an average of the classifier performance. For instance, assume that there are 10 classifiers. Consider that for user 1 (true identity), 9 out of 10 classifiers bring in rank 1 while the 10^{th} classifier got in rank 100.Final fused rank for user 1 is R1=109, similarly consider for other user 2, 9 out of 10 classifiers result in rank 5 while the 10^{th} classifier result in rank 15.Final fused rank for user 1 is R2=60, as per Borda count approach the final identity, R1 (corresponding to true identity) won't be chosen. This generally occurred due to the presence of only one weak classifier.

- Weighted Borda Count Method: This method is a modification of the Borda count approach in which ranks of individual matchers are obtained the respective weight. The fused rank scores in weighted Borda count method are computed as follows:

$$R_k = \sum_{i=1}^{M} w_i r_i(k) \qquad (5)$$

Where w_i represent the weights assigned to the i^{th} matcher.

- Bucklin Majority Voting: The fundamental principle of this technique is based on majority voting system, in which, if in the first place any user obtained the majority vote, then that user gets elected; otherwise it added the second preference votes and again the operation is repeated. The procedure is repeated until the entire claimed user gets some rank.
- Nonlinear Weighted Ranks: In this approach the user identities ranked list produced by various matchers are nonlinearly weighted and combined. The following fusing methods comes under this category:

$$R_k = \sum_{i=1}^{N} \tanh\left(w_i r_i(k)\right) \qquad (6)$$

$$R_k = \sum_{i=1}^{N} \exp\left(w_i r_i(k)\right) \qquad (7)$$

$$R_k = \sum_{i=1}^{N} w_i \exp\left(r_i(k)\right) \qquad (8)$$

Where $r_i(k)$ represent the rank authorized to user k by the i^{th} matcher, and w_i represent the weights assigned to the i^{th} matcher.

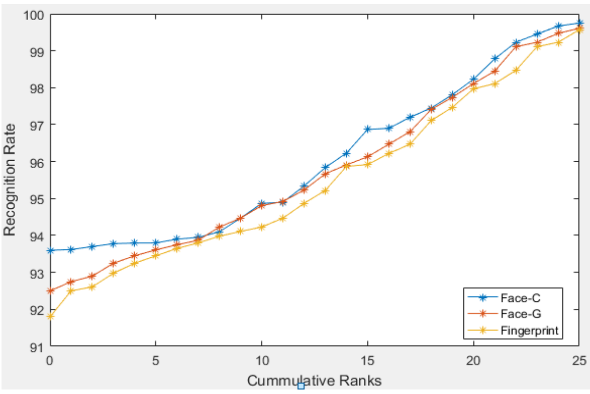
IV. EXPERIMENTS AND RESULTS

In this section we mainly focus on a multibiometric system based on multi-algorithm and multimodal systems.

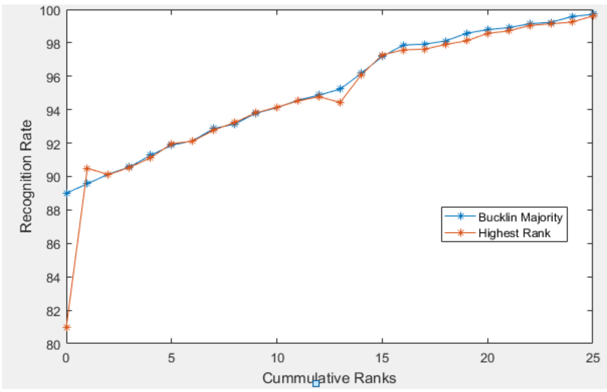
4.1 Results from multimodal system:

For experimental evaluation NIST BSSR1 is used as a database of multimodal biometric from the NIST (http://www.itl.nist.gov/iad/894.03/biometricscores/bssrl_contents.html). NIST BSSR1is a multimodal database consists of matchers of fingerprint and face.

This dataset consist of a 6000 subjects, which is more sophisticated compared to other multimodal biometric dataset which is publicly available. NIST BSSR1 dataset comprises of the three partitions. The initial segment of this dataset comprises of matching scores from face and fingerprint with 600 subjects. The individual subject right index finger is utilized to form the fingerprint scores dataset. At the same time, the matching scores of faces namely face-C and face-G are generated from the frontal face images of the same subjects. For training purpose, the first 100 subjects matching scores were used, to evaluate the performance of the system dependent on different rank level fusion technique the rest 500 subjects were utilized as independent test data to ascertain the performance. The CMC (Cumulative match characteristic) curve from the respective three matchers comparable to the independent test data (500 subjects) is presented in Fig. 1 (a). The approximated weights were used in this observation were as follows: $\omega_1 = 0.3$,$\omega_2 = 0.3$, $\omega_3 = 0.4$ for weighted Borda count; $\omega_1 = 0.4$, $\omega_1 = 0.3$, $\omega_1 = 0.3$ for nonlinearly weighted ranks (Non –Linear (1)) as in (10) ; $\omega_1 = 0.3$, $\omega_1 = 0.4$, $\omega_1 = 0.3$ for nonlinearly weighted ranks (Non –Linear (2)) as in (11) ; where the ω_1 represents the weights for Face C matcher, ω_2 for Face G matcher, ω_3 for fingerprint matcher. The CMC curves from the rank level combination utilizing a different combination approach are shown in Fig. 1 (b), 1 (c) and 1 (d).



(a)



(b)

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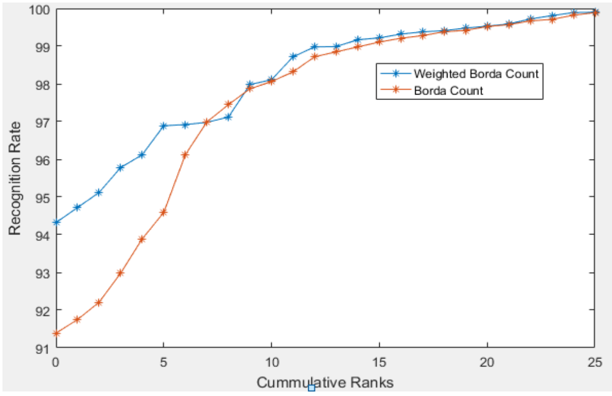
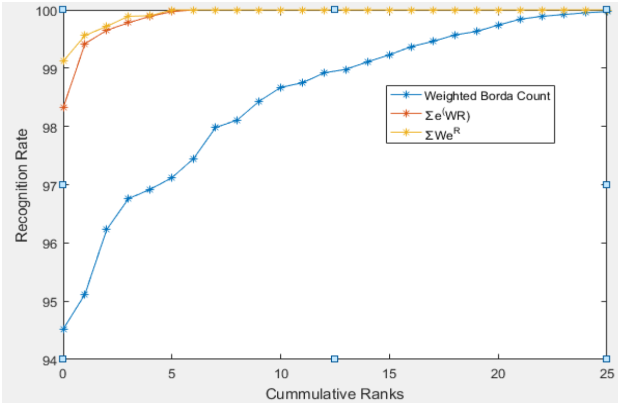


(c)



(d)

Fig. 1. CMC curves for unimodal system in (a); the CMC curve using Bucklin and Highest Rank method in (b); CMC curve using weighted Borda and Borda count method in (c), and CMC using different non linear rank level methods in (d).

Table 1. Performance of proposed technique from NIST BBSR1 Fingerprint and Face Database (600 Subjects)

	Weighted Borda	Non -Linear (1)	Non -Linear (2)	Borda	Bucklin	Highest Rank
1st Rank	94.4	98.32	99.12	91.4	89.0	81.0
2nd Rank	94.8	99.42	99.56	91.7	89.5	90.8
3rd Rank	95.3	99.65	99.72	92.3	90.5	89.9

4.2 Results from multi-algorithm system:

The exhibition of the proposed framework is assessed on palmprint based multi-algorithm system from publicly available Hong Kong Polytechnic University palmprint database (http://www.comp.polyu.edu.hk/~biometrics/) .This database consists of the hand images gathered from the students and staffs , total of 4992 palm images from around 350 individuals. The database contains all the subjects in the age between 12-57 years. In this set of experiments, we utilized 2890 images, which are organized into the right hand group. These images have scale variation, high pose and translation shown in Fig. 2.

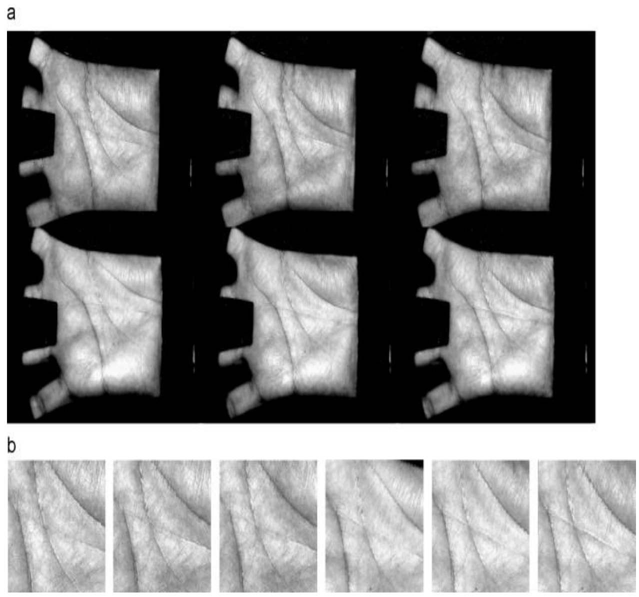


Fig. 2. Palmprint image samples from PolyU Palmprint database in (a); their corresponding segmented images in (b)

The noise in the palmprint images is reduced by preprocessing step and to smoothen the image we employed Adaptive median filter [33]. The main advantages with this filter is that it preserved the particulars while smoothing noise of non-impulsive type which, in natural is not found in traditional filter. After pre-processing the next step is the extraction of ROI (Region of Interest) from the segmented portion. In this experiment we captured segment of 150 × 150 pixel palmprint images (see Fig. 3). There are several unique features (Principle line, Wrinkles, ridges and texture pattern) which can be used for feature extraction process. We examined three feature extraction methods, which have appeared to offer encouraging outputs in the study. First, Canny edge recognition strategy is one of the standard edge identification procedures. In 1983, initially it was first invented by John Canny for his Master's thesis at MIT, and still performed well when it compared to other algorithms that have been developed. To discover edges by isolating noise from the picture before discovers edges of the picture the Canny is a significant technique. The canny technique is a superior technique without troubling the features of the edges in the image subsequently it applies the tendency to discover the edges and the genuine value for the threshold. The Canny edge detection algorithm is outlined to subsequent steps:

- The First step involves with before edge detection, refine the noise from an original image. Using Gaussian filter the Image is first smoothed.
- Calculate the edge durability by using image gradient. Execute 2D spatial gradient measurement on an image sing a Sobel operator.
- Calculate the edge strength at each point (absolute gradient magnitude). Using Sobel operator calculate the gradient in x (columns) and y directions (rows)

$$G = \sqrt{G_x^{\ 2} + G_y^{\ 2}} \tag{9}$$

$$\theta = arc\ \tan\left(\frac{G_y}{G_x}\right) \tag{10}$$

- Find the edge direction by using the gradients in x and y directions applying a formula $\theta = \tan^{-1}\frac{G_y}{G_x}$
- Describe the edge heading to a direction that can be outlined in an image. The heading can be in any of the four bearings in 0, 45, 90, 135 degrees encompassing a pixel.
- Knowing the edge bearings apply non greatest concealment which is utilized to follow along the edge in the edge heading and smother any pixel esteem which isn't viewed as an edge. A thin line is given in an output image.
- Hysteresis is applied to recognize the genuine edges at whatever point there is a separating of an edge form.

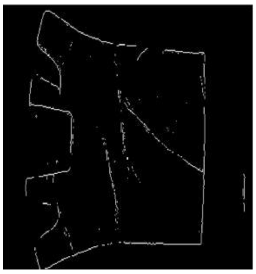
Canny edge detector initially smoothens the picture to wipe out any noise, and afterwards it finds the picture inclination to feature areas with higher subsidiaries. The image segments with greater derivatives are followed by the algorithm to suppress any pixel that is not at the maximum. Two thresholds T1 and T2 are then presented. If the weight of the threshold is under T1, it is fixed to zero (none edge). If the weight is above T2: it is fixed an edge. And if the weight is among the two thresholds, then it is set to zero otherwise there is a path from this pixel to a pixel having a weight above T2.Second, Gabor filter technique was initially proposed by Daugman in 1980.The distinctive palm images may have identical principle lines, so it isn't adequate to produce particular by utilize the principle line only. The palmprint texture feature regularly has more information about a particular. In this proposed method Gabor filter technique is utilized to extract the texture feature by capturing the frequency and orientation information from the image. The 2-D Gabor filter strategy is characterized as:

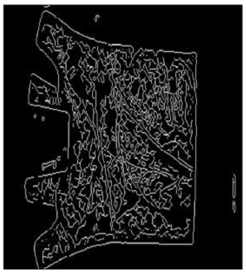
$$G(x, y, \theta, u, \sigma) = \left(\frac{1}{2\pi\sigma^2}\right) \times \exp\left\{-\frac{\sqrt{x^2+y^2}}{2\sigma^2}\right\} \times \exp\{2 \times \pi \times i \times u(x\cos\theta + y\sin\theta)\} \tag{11}$$

Where x and y are represented the coordinate of the filter, θ is the orientation of the function, u is the frequency of the sinusoidal wave, σ is the Gaussian envelope and $i = \sqrt{-1}$. In this experiment we got the optimized value of Gabor filter with $u = 0.1798\ and\ \sigma = 7.0$ at an orientation of 45^0.

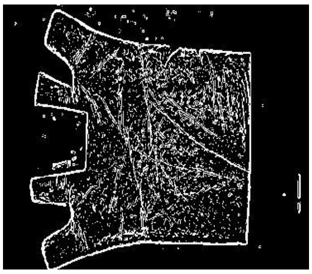
$$I_\theta(i,j) = \sum_{x=1}^{w}\sum_{y=1}^{w} G_\theta(x,y)\, I(i-x, j-y) \tag{12}$$

Where I_θ is the image at θ orientation, I is the input image and Gabor filter mask having the size $w \times w$.The Gabor filter is utilized on 150×150 size ROI to get the corresponding segmented image. Fig. 4 represents the feature extraction for palmprint using three different algorithms. Third, Multi scale Edge Detection method was proposed by Mallat in [34] shows that multi scale edge detectors mild the signal at different scales and can be able to detect the sharp variation points from their first or second subordinate.





(A) CANNY EDGE DETECTION **(B) GABOR FILTER**



(C) MULTI SCALE EDGE DETECTION

FIG. 4. FEATURE EXTRACTION FOR PALMPRINT USING (A) CANNY EDGE DETECTION (B) GABOR FILTER (C) MULTI SCALE EDGE DETECTION

The efficiency of the proposed algorithm is represented in Fig.5 and it shows that the Multi Scale Edge Detection algorithm has the maximum efficiency of 96% compared to Gabor filter with 88% and Canny Edge detection with 70%.

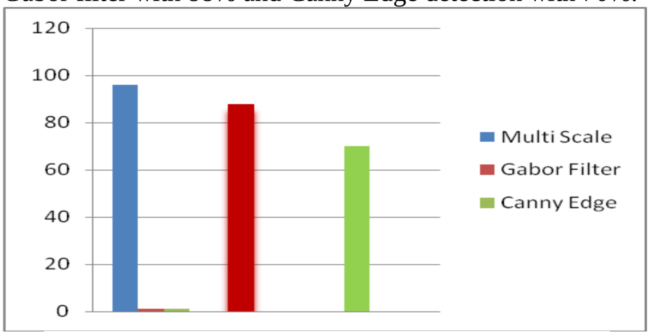


Fig. 5. Comparison of efficiency by different algorithms

Matching algorithm in biometric is utilized to discover the likeness between two given data sets. It achieved a matching score, which is commonly floating point value after taking input as a query sample to be verified with the reference sample from the database. The asserted client is viewed as validated if the generated match score value is greater than the pre-established threshold value. In this paper, we use the correlation function as a template matching technique which is a common and practical technique used in many pattern recognition applications. Consider a query sample x with values $\{x_1, x_2, \ldots, x_n\}$ and a template sample y with values$\{y_1, y_2, \ldots, y_n\}$, a correlation function is utilized to find the similarity between the two feature vector as follows:

$$R_{x,y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sigma_x \, \sigma_y} \quad (13)$$

Where $\bar{x}$,$\bar{y}$ denotes the mean value for the sample x and y respectively and σ denotes the standard deviation. The degree of correlation between the two samples is denoted by R . R having the value 1 indicates that both samples are perfectly identical, value 0 indicates that they are perfectly independent and value -1 indicates that they are completely opposites. In our analysis we at first did the authentication by figuring the matching score for canny edge, Gabor filter and Multi scale detection technique. Table 3, 4 and 5 represent the summary of the matching score obtained from more than one images of a single individual utilizing the canny edge, Gabor filter and Multi scale technique.

Table 3 Matching score using Canny Edge Detection Technique

	2	3	4	5	6	7	8
1	0.9256	0.9137	0.8435	0.922876	0.7613	0.7781	0.7615
2		0.9250	0.8478	0.91567	0.7523	0.7734	0.7534
3			0.8878	0.90673	0.7467	0.7623	0.7656
4				0.89674	0.8134	0.7523	0.7434
5					0.7234	0.7789	0.7356
6						0.8960	0.7545
7							0.7956

Table 4 Matching score using Gabor Filter Technique

	2	3	4	5	6	7	8
1	0.9746	0.9843	0.9789	0.9867	0.6627	0.6771	0.7234
2		0.9745	0.9578	0.9756	0.6523	0.6645	0.7323
3			0.9723	0.9645	0.6432	0.6023	0.7543
4				0.9534	0.6763	0.6523	0.7234
5					0.7156	0.7089	0.7213
6						0.6543	0.7323
7							0.8089

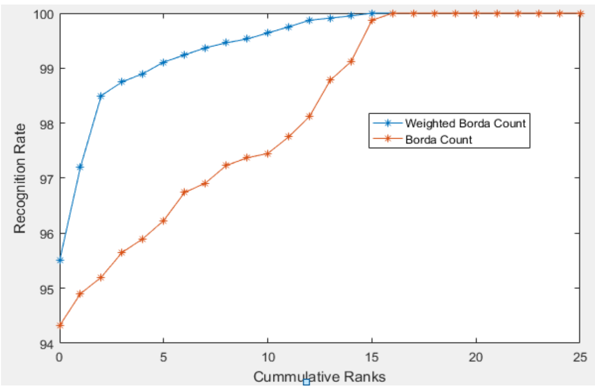
Table 5 Matching score using Multi Scale Detection Technique

	2	3	4	5	6	7	8
1	0.9923	0.9887	0.9823	0.9978	0.7532	0.6877	0.7145
2		0.9866	0.9645	0.9823	0.7456	0.6732	0.7367
3			0.9889	0.9578	0.7332	0.6225	0.7456
4				0.9432	0.7789	0.6576	0.7354
5					0.7098	0.7076	0.7543
6						0.6435	0.7432
7							0.8324

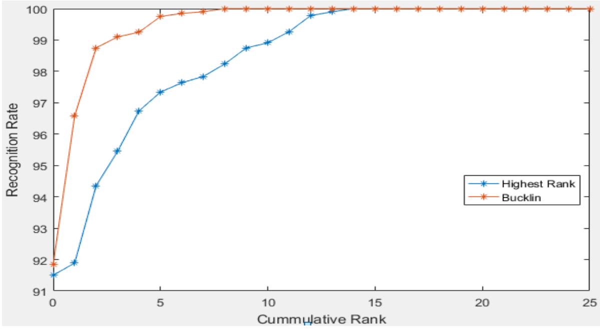
To upgraded the overall system performance we utilized rank level fusion strategies which combined the different ranks output by three palmprint feature extraction algorithm (Canny detection, Gabor filter and Multi Scale Detection technique) using the different rank combination schemes namely Highest rank method, Borda count, weighted Borda count, Bucklin Majority Voting and Nonlinear weighted rank. For training purpose the first 150 individuals matching scores were utilized, to assess the outcomes of the system dependent on various rank level fusion strategy the rest 200 subjects were utilized as independent test data to find out the exhibition.

The CMC (Cumulative match characteristic) for the experimental result of the weighted Borda count and Borda count is shown in Fig. 6(a). The approximated weights for the weighted Borda count were used in the experiments were $\omega_1 = 0.2$, $\omega_2 = 0.675$, $\omega_3 = 0.125$, respectively, for the Canny edge, Gabor filter and Multi scale detection feature. The CMC (Cumulative match characteristic) curve for the experimental result of Bucklin and Highest Rank approach is shown in Fig. 6 (b). The CMC (Cumulative match characteristic) for the experimental result of proposed non-linear as in (9), (10) and (11) is shown in Fig. 6 (d). The Rank-one recognition performance produce by Bucklin approach is poor, while for other rank (ranks>=2) it is found consistent improvement.

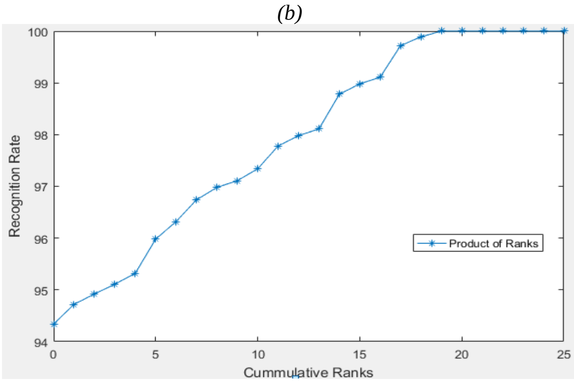
The estimated weight assigned for the non-linear approach are as follow: $\omega_1 = 0.1$, $\omega_2 = 0.675$, $\omega_3 = 0.225$ for tanh ,i.e., using non-linear approach as in (9); $\omega_1 = 0.275$, $\omega_2 = 0.4$, $\omega_3 = 0.325$ for nonlinearly weighted ranks (Non –Linear (1)) as in (10) ; $\omega_1 = 0.4$, $\omega_1 = 0.375$, $\omega_1 = 0.225$ for nonlinearly weighted ranks(Non –Linear (2)) as in (11) ; where the ω_1 represents the weights for palmprint matcher produce by Canny edge Detection technique, ω_2 for palmprint matcher produce by Gabor filter technique, ω_3 for palmprint matcher produce by Multi scale Detection technique. The CMC curves from the rank level fusion using a different fusion approach are shown in Fig. 6 (b), 6 (c) and 6 (d). The experimental results from Fig. 6 (a) shows that weighted Borda count performed significantly improvement as compared to Borda count approach. Table 6 represents the summary of the results produced by different rank level combination approach. The average Rank-1 identification rate from weighed Borda count approach is 97.1%, which are showing significant improvement as compared to Borda count approach with 94.8% of the average Rank-1 identification rate. It is obvious from the outcomes that the non-linear approach outperformed than the other rank combination schemes, among the non-linear approach Non-linear (2) as in (11) accomplishes the best achievement (average rank-1 rate of 99.5%) as compared to Non-linear (1) as in (10) with average rank-1 rate of 98.3%.



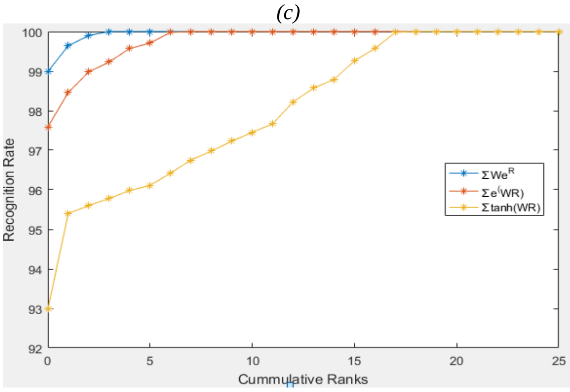
(a)



(b)



(c)



(d)

Fig. 6. CMC curve using weighted Borda and Borda count method in (a); the CMC curve using Bucklin and Highest Rank method in (b); CMC curve using product of Ranks in (c), and CMC using different non linear rank level methods in (d).

Table 6: Performance of proposed technique from Hong Kong Polytechnic University database of palmprint

	Weighted Borda	Non-Linear (1)	Non-Linear (2)	Borda	Bucklin	Highest Rank	Product of Ranks
1st Rank	95.6	97.6	99.0	94.4	92.0	91.6	94.4
2nd Rank	97.3	98.5	99.6	94.9	96.6	92.1	94.6
3rd Rank	98.6	99.0	99.9	95.3	98.8	94.4	94.9

V. DISCUSSION

In this section we discuss about the performance analysis of multimodal and multi-algorithm system based on rank level fusion. The experimental result based on multimodal system is shown in Table 2.

The result shows a significant improvement as compared to other rank level fusion technique. As compared to other schemes the non-linear approach achieved a maximum identification rate, the average Rank-1 rate produced by the proposed non-linear approach is 99.4% for Non-linear (2) and 99.1% for Non-linear (1) approach, whereas it achieved 94.8% average rate for the weighted Borda count and 91.8% for the Borda count approach. The test results from the rank level fusion utilizing Bucklin approach and Highest Rank methodology is appeared in Fig. 2 (b). The exhibition of the Bucklin approach is indicated superior to that of Highest Rank methodology. The experimental results from the rank level combination using the Weighted Borda count approach and the Borda count approach is shown in Fig. 2 (c) .The performance from the Weighted Borda count is shown better than that of Borda count approach. The experimental result of a non-linear approach as in (10) and (11) is shown in Fig. 2(d). The presentation of the Non-linear (2) method is indicated better than that of Non-linear (1) method.

The experimental result based on multialgorithm system is shown in Table 6 the average Rank-1 rate produced by the proposed non-linear approach is 99.0% for Non-linear (2) and 97.6% for Non-linear (1) approach, whereas it achieved 95.6% average rate for the weighted Borda count and 94.4% for the Borda count approach. The test outcomes from the rank level combination using Bucklin approach and Highest Rank approach is presented in Fig. 3 (b). The presentation of the Bucklin approach is indicated superior to that of Highest Rank methodology. The experimental results from the rank level combination using the Weighted Borda count approach and the Borda count approach is shown in Fig. 3 (a) .The performance from the Weighted Borda count is shown better than that of Borda count approach. The experimental result of a non-linear approach as in (10) and (11) is shown in Fig. 3(d). The performance of the Non-linear (2) approach is shown better than that of Non-linear (1) approach. The Rank-1 identification rate of 99.12% is achieved using Non-linear (2) approach in the case of multimodal system, whereas it was 99.0% using Non-linear (2) approach in the case of multi-algorithm system. The Rank-1 identification rate of 91.4% is achieved using Borda count approach in the case of multimodal system, whereas it was 94.4% using Borda count approach in the case of multi-algorithm system. The Rank-1 identification rate of 94.4% is achieved using weighted Borda count approach in the case of multimodal system, whereas it was 95.6% using weighted Borda count approach in the case of multi-algorithm system.

VI. CONCLUSION

The proposed paper provides a comparative analysis performance of multimodal and multi-algorithm system based on rank level fusion. This paper deals with the different rank combining scheme, including , Highest rank, Borda count, weighted Borda count, nonlinear weighted approach(tanh, Non-linear1and Non-linear2) and Bucklin methods utilized in the application of multibiometric (multimodal, multi-algorithm) , the primary objective of this investigation is to talk about the procedure and approaches utilized in various rank combining scheme to improved the system performance. It is also discussing the different rank combining scheme for NIST BSSR1 multimodal database of fingerprint and face produce by three matcher of Face-C, Face-G and fingerprint and multialgorithm (Hong Kong Polytechnic University database of palmprint) by combining the three matcher of Canny edge detection, Gabor filter and Multi scale Detection technique . A combination dependent on rank level, be that as it may, another and fundamentally understudied issue, which has the abilities to diminish the issues confronted with the instance of score level combination. Our exploratory outcomes given in this paper demonstrate that enhancement in the identification accuracy can be accomplished when contrasted with those from unimodal frameworks. The outcomes likewise uncover that combination of individual modalities can improve the general execution of the biometric framework. The experiment based on multimodal (NIST BSSR1 multimodal database of fingerprint and face) and multialgorithm (Hong Kong Polytechnic University database of palmprint) system shows an improvement in term of the Rank-1 identification rate of the system.

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