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Multi-modal palm-print and hand-vein biometric recognition at sensor level fusion

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ABSTRACT

When it is important to authenticate a person based on his or her biometric qualities, most systems use a single modality (e.g. fingerprint or palm print) for further analysis at higher levels. Rather than using higher levels, this research recommends using two biometric features at the sensor level. The Log-Gabor filter is used to extract features and, as a result, recognize the pattern, because the data acquired from images is sampled at various spacing. Using the two fused modalities, the suggested system attained greater accuracy. Principal component analysis was performed to reduce the dimensionality of the data. To get the optimum performance between the two classifiers, fusion was performed at the sensor level utilizing different classifiers, including *k*-nearest neighbors and support vector machines. The technology collects palm prints and veins from sensors and combines them into consolidated images that take up less disk space. The amount of memory needed to store such photos has been lowered. The amount of memory is determined by the number of modalities fused.

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1. INTRODUCTION

With the increased demand for information security, the insecure traditional methods of authentication and data access are no longer adequate. These strategies have been phased out due to the advancement of biometrics. Biometrics is a computerized security method that relies on a human's unique physiological traits to authenticate or identify his or her identification. Acceptance of a biometric feature is dependent on its consistency. Fingerprints last a lifetime, whereas face appearance might alter dramatically due to a variety of causes such as age, disease, and so on.

The data from the biometric modality is collected by a sensor in the basic biometric system. The biometric system must also have an algorithm for extracting biometric features, a matching element for comparing the template to the extracted features, and a decision-making process for verifying the presence identity. Furthermore, universality, uniqueness, durability, collectability, and acceptability are also required biometric characteristics.

Biometric systems are often uni-modal, relying on proof from a single source of data feature to authenticate a person. Clutter in the attained records, intra-class variation, and inter-class proximity are all issues that a system with a single source must contend with. The rate of mistaken acceptance and rejection has increased as a result of this issue [1]–[4]. Biometric systems have the propensity to solve some of the problems (intra-class variations). Multi-biometric systems can make a significant difference in overall reliability since they are made up of multiple forms of biometrical data which are made up of multiple extracted features.

Multi-biometrics is a method of combining several types of biomedical data. The stages of the fusion mechanism can be summarized as follows. Multi-modal is the procedure used to extract various biometric information from an individual, such as a fingerprint or a vein in the hand, which necessitates the use of multiple sensors. Multi-sample is the process of acquiring several readings over the course of registration or authentication, such as multiple face readings from the same person [5]–[7]. It has numerous procedures, in which, for the same biometric sample, different methods for characteristic separation and matching are used. Multi-instance is the process of collecting several samples of the same biometric. The result is referred to as multi-instance, for instance, finger lump motifs of more than one finger. Finally, there are multi-sensors, in which more than one sensor can be used to capture the same biometric data [8].

Multi-sensor data fusion is a developing technology that is used by the department of defense (DoD) in areas like automated target recognition (ATR), identification-friend-foe-neutral (IFFN), and others. Medical diagnosis, smart buildings, and other non-DoD can also use multi-sensor fusion [9]. Multi-sensor data fusion mechanisms can be used in simpler applications such as signal processing and pattern recognition.

Despite the importance of multimodal biometrics research, it has primarily concentrated on higher level fusion. Due to the intricacy of the picture registration process, sensor level fusion produces valuable information, which leads to more accurate outcomes than higher level fusion [10]. Because the data retrieved from images may be sampled at different arrangements, resampling is a necessary step before pixel data integration to achieve a high level of registration.

By merging data at sensor levels, this study attempts to assess the achievement of two biometric modalities. This study attempts to compare two biometric modalities at the sensor level in order to assess their performance. The remainder of the article is structured as follows: The primary motivational principles that guide this study are presented in section 2. The literature on related current systems is presented in section 3. Section 4 conveys a description of the proposed strategy. The thorough experimental data are available in section 5. Finally, the conclusion is ultimately brought up in section 6.

2. MOTIVATION AND CONTRIBUTION

Data from embedded images have been employed in a variety of applications to increase overall system performance over data gathered by a single sensor. A wide range of applications has used data from fused images to improve overall system performance. Images recorded from several sensors can be combined to create a composite image, which is better or even equal to a standalone image. The stages needed in fusing data from several sensors into a fused one may differ depending on the method of fusion (low-level or high-level).

There has been a lot of studies on multi-sensor data fusion for a wide range of applications, according to the literature. However, compared to a higher level of fusion, such as score and decision, there is a little of studies in the field of biometrics at the sensor level fusion, because, at these levels, the images of different modalities must be saved separately, necessitating a lot more space. As the template must be safeguarded and regenerated for numerous modalities on a frequent basis, this needs additional overprotection. Therefore, the proposed sensor-level fusion in this study is capable of producing a consolidated template. As a result, making consolidated images that require less memory is possible. The quantity of memory allocated for image storage is determined by the number of modalities to be fused; when compared to individual preserved photos, the memory required for two modalities is reduced by 50%. In addition, this research looks at how compound fusion influences an individual’s verification process at the sensor level rather than at the higher level. The effectiveness of the three merging strategies is evaluated. At the sensor level, experiments on over 100 different subjects from publicly available databases demonstrated that combining feature level, match score level, and decision level fusion beat the three strategies individually.

3. LITERATURE REVIEW

As stated in section 2, there is a limited number of studies in the field of biometrics at the sensor level fusion when compared to a higher level of fusion such as the assignment of scores and making decisions based on the extracted characteristics. Moreover, the amount of data produced by contemporary biometric fusion systems tend to decrease as you progress through the biometric modules. Excessive information is present in raw data obtained at the sensor level, whereas information created at the decision level (higher levels) is a simple decision that either accepts or rejects the authentication attempt.

Higher-level data must be elicited, such as raw fingerprint scans or feature sets like minutiae. However, creating raw data from off-the-shelf biometrics is difficult. Biometric data in its raw form frequently comprises duplicate information and features acquired from a range of sources, and it may not be consistent. As a result, sensor and feature levels are less problematic as compared to higher levels. Higher levels simply mean the process of rejection or acceptance of raw fingerprints after being analyzed and accepted. Fusion of obtained data and match scores at the verification stage is less difficult than fusion during the earlier stages.

Noore *et al.* [11], for instance, introduced a mathematical biometric fusion algorithm that uses multi-level discrete wavelet transformation to fuse information from four separate biometric images into a single composite image. According to the authors, the algorithm can successfully detect popular tampering attacks that may occur at the authentication stage of an individual. The algorithm also promises a reduction in the amount of memory required by 75%. Using a 3-stage hybrid biometric template, Chin *et al.* [12] developed a multi-biometrics system in which the palm-print and fingerprint are fused at the feature level in the first stage. The hybrid template is protected in the second and third stages. As claimed by the experimental outcomes, the results show that their technique can narrow the resulting distribution range.

In a multimodal biometric system, Veeramachaneni *et al.* [13] offered an approach for determining the fusion rule and sensor thresholds. The approach presented focuses on system correctness. The proposed solution was created to address any issues that may develop in a biometric system that is primarily utilized for security authorization.

Connaughton *et al.* [14] described a method for evaluating three iris sensors against a similar number of iris matching systems. They also investigated the impact of cross-sensor matching performance against single-sensor matching. The sensors were evaluated using three distinct matching algorithms, with conclusions based on the interaction between the matching algorithm and the cross-sensor and single-sensor.

Janani and Saravanakumar [15] described a dual security identification system using a multi-feature identification method based on fingerprints and palm-prints. There are three sorts of image and minutiae extraction queries in the suggested approach. They used a strategy that looked at the distinguishing power of several combination traits and discovered that density is particularly helpful for palm-print recognition.

Pan *et al.* [16], [17], on the other hand, have used a variation of biometric system that is considered with authorizing individuals in a voting process. A multi-part ballot was used to authenticate the identity of candidates. The authentication was performed using numerous matching stages. The ultimate outcome was decreasing the risk of compromising a couple of identities during a ballot distribution stage. Shdefat *et al*. [18] proposed a human identification approach based on a distinct type of biometric method. Their method relies on the waveform of an electrocardiogram (ECG), which is then translated into features. Using electrodes inserted on the body, the waveform is derived from the electrical activities of the individual's heart. This strategy, however, has not shown to be reliable, owing to the difficulty of connecting the particular instruments that read cardiac pluses.

Patil and Bhalke [19] proposed a multi-modal system that combines fingerprint, handprint, and iris recognition. For each of these traits, a matching score was determined using the presented technique. The authors also proposed utilizing a weighted fusion technique to combine these single features. According to the authors, a 95.23% accuracy was attained, which is higher than previous methods at the time. Sanjekar and Patil [20] also recommended employing a fingerprint, palm-print, and iris to validate a person's identity. To extract features, the wavelet transfer method was utilized. Principal component analysis (PCA) is used to shrink the dimensionality. Attribute fusion is used on three levels: at the feature level, at the feature level with the match score level, and at the feature level with the decision level. Kant and Chaudhary [21] on the other hand, presented a new biometric system. Merging several features at a high-level fusion was also involved. The three features were: finger Knuckle print, fingerprint, and handprint. After the user is identified, he/she is announced as real or deceitful using score fusion. The findings of the experiments were utilized to demonstrate the effectiveness of the system using several classification methods.

Naderi *et al.* [22] proposed a tri-modal biometric recognition system for iris, handprint, and fingerprint recognition. To match the fingerprint, minutiae extraction was used along with the use of well-known merging methods. Maximum inverse rank (MIR), a novel incorporation algorithm, has also been proposed, which is beneficial for both changes in scores and low ranking. In comparison to current recognition systems, the actual results demonstrated the usefulness of this method.

Mhaske and Patankar [23] demonstrated a multimodal biometrics system that combines a fingerprint and a palm print. Pre-processing has been used to improve the feature of the input image in their method. The system then employs feature-level fusion for each trait. The classification was then done using the Euclidean distance approach. The results of the study revealed that the proposed system outperformed the single modal system. Kale and Gawande [24] developed an approach for use in human recognition applications. In the training phase, fingerprint and handprint photos are used independently. In addition to ordinary cameras, night vision cameras were used to collect the photographs. Image enhancement techniques were used to enhance these photos. In addition to the features that are extracted, the quality basis is integrated. A unique dataset was proposed in their paper, which enhanced system performance and accuracy by 90-95%.

Sanjekar and Patil [25] presented a method based on a palmprint and fingerprint combination, as well as the fusion of both features at the feature and score levels. Both properties were determined using directional energy feature vectors, which were then merged to create a single feature vector that was then used as a distance classifier. Matching scores for specific workbooks are combined using group and product rules in a score level merging process. On the total and product bases, the equal error rate (EER) has been obtained at 0.538 percent at the feature level which outperforms the EER of 0.6141 percent at the score level, respectively. Similarly, Ali and Gaikwad [26] explored the identification technique for fingerprints and palm prints. The details of each feature have been highlighted separately. Each aspect is processed using several techniques which were discussed thoroughly in their biometric authentication system. The next section proposes a sensor-level biometrical authentication system that works despite the difficulty of recording the image, based on the limitations that have been explored in literature, which only focus on fusion at the upper levels.

4. PROPOSED METHOD

Two hand-based biometric features namely finger and palm prints were used in this study. These two characteristics are known as modalities. The Log-Gabor approach was employed in both modalities in this strategy. The Log-Gabor algorithm is used to create texture images. The proposed system's main premise is that it will be implemented at the sensor level rather than at higher levels in subsequent phases, as stated in earlier suggestions in the literature.

To begin, Log-Gabor was employed to extract characteristics from two single solitary modalities, namely finger and palm prints. Second, the same method was used to extract features from fused images that combined both modalities, allowing for a more comprehensive understanding of the distinction between single and fused modalities. At this point, a decision can be made based on the success percentages of both strategies. Third, to optimize the recovered features from the mosaic images, the well-known dimensionality reduction PCA is applied (i.e. fused images of the two modalities). Linear weighted *k*-nearest neighbor (*k*-NN) and linear/non-linear support vector machines (SVMs) were employed for classification. Finally, the tabulated data gathered from the tests is used to validate the proposed authentication multi-biometric system. The tabulated statistics also demonstrate why such a system can be implemented at the sensor level.

4.1. Multibiometric systems

4.1.1. Database description

A sample image from an open-source database is used to test the proposed multimodal biometric system. Palm print PolyU and other fingerprint databases have been used in particular. The databases contain a high-resolution set of profiles as well as the photographs associated with them. We took a total of 100 users and 5 samples from the palm print PolyU database, which has 100 users and 10 sample photos for each individual user, and the fingerprint database, which has 168 users and 5 sample images for each individual user. Three of the five samples were utilized for training and two were used for testing.

4.1.2. Biometric systems

It is necessary to explore the core principle behind biometric systems in general in order to comprehend the proposed method. The conversation then shifts to a discussion of the methodology that undermines the proposed system. In its most basic form, a biometric system is a pattern recognition system that analyzes biometric qualities in order to extract information that can be used to identify an individual during the matching stage. A biometric system is made up of four main components: i) a sensor module that collects biometric information; ii) a feature extraction module for extracting the feature set from the acquired data; iii) a matching module that compares feature vectors to the database template’s counterparts; iv) a decision-making module that determines whether or not the confirmed user’s identification is approved [27].

There are two modes of operation for biometric systems: i) enrollment which entails eliciting specific qualities from users and putting them in database templates and ii) authentication: which determines whether a user is allowed to access a system by comparing unverified identity traits to those stored in the database.

4.2. Fusion levels

In domains like medical image processing, computer vision, and so on, image fusion is an interesting issue. The fusion technique’s goal is to describe and transmit the input pictures while keeping the information in the combined image. Sensor fusion is the process of combining data from various sensors in order to improve the performance of an application. The words ‘sensor fusion’, ‘data fusion’, ‘information fusion’, ‘multi-sensor data fusion’, and ‘multi-sensor integration’ have been widely used in the literature to describe data acquired from many sources. Wald [28] offers the term ‘data fusion’ as a generic name for fusion. As a result, sensor fusion does not demand inputs from numerous sensors; rather, it is a combination of data or data obtained from sensors.

Fusion processes are divided into three separate levels: low, moderate, and high-level fusion. Fusion at the low/raw data level combines various raw data to produce new information. It is expected that the outcome data will contain more information than the original data. Fusion at the intermediate/feature level combines a variety of features. Fusion at the high/decision level combines the decisions of multiple experts. For decision fusion, a variety of methods can be utilized, including voting, fuzzy logic, and statistical methods.

4.3. The proposed system

The suggested system focuses on the fusion of multi-biometrics that makes up decisions at the sensor level. The system has two modes: enrollment mode and verification mode. In enrollment mode, two different data modalities are supplied to the system after being captured by the sensor. The raw data are then merged to form a mosaic image, as illustrated in Figure 1. After that, a feature extraction method is used to extract the features from the mosaic image, and the extracted feature sets are saved in a database to be used in the matching process later.

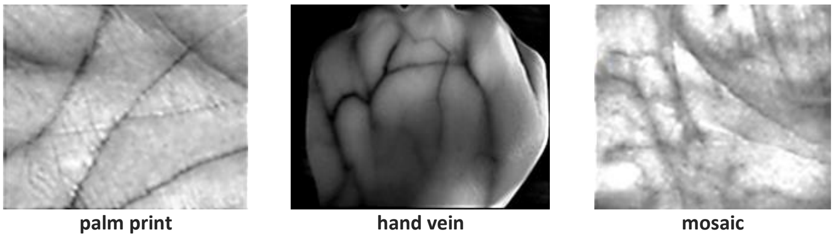

Figure 1. The mosaic image

The same modalities are delivered to the system by one sensor during the verification step, and the raw data are then fused to form a mosaic image. Following that, the same feature extraction method is used to extract features from the mosaic image, and the extracted features are compared to the sets stored in the database to produce a matching score based on the matching process, after which a judgment is made (accept/reject). Figure 2 depicts the suggested sensor level system.

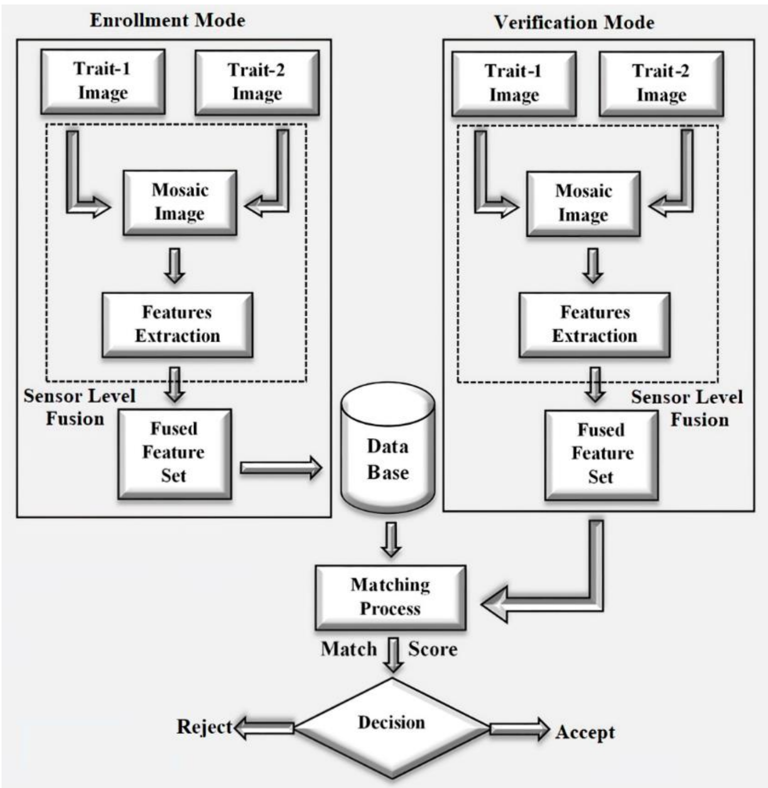

Figure 2. The suggested fusion at sensor level

4.4. Feature extraction

This section delves deeper into the feature extraction methods that are used to extract features prior to training the classifier. Filters are used to provide important descriptions of images in terms of multiple variables. The set of filters used in the proposed system is mainly Log-Gabor and PCA.

4.4.1. Log-Gabor filters

The Log-Gabor [29] filter demonstrates that Gaussian transfer meanings are an efficient approach to describe input images. Information about frequency is stored locally. When compared to the original Gabor filter, this information provides a decent set of features. As illustrated in (1), the Log-Gabor function has the transfer function (1),

$$G(\omega) = exp\left(\frac{-log\left(\frac{\omega}{\omega_0}\right)^2}{2\left(log\left(\frac{\sigma}{\omega_0}\right)\right)^2}\right) \tag{1}$$

where ω_0 is the filter's center frequency, a constant shape ratio can be obtained using the value σ that must be held constant for the different values of ω_0. The frequency reaction to the original Gabor filter in contrast to Log-Gabor filter is shown in Figure 3.

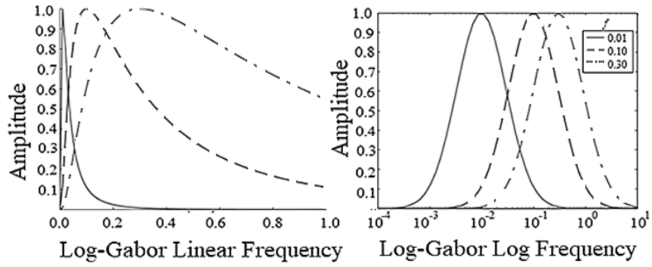

Figure 3. Frequency response of the Log-Gabor filter vs the original

4.4.2. Dimensionality reduction and PCA

Reducing data dimensions to a sub-space with fewer dimensions to boost computational performance while keeping the majority of the information is frequently, the desired goal. In the proposed system, a set of data associated with particular entities that can be found on the hand-vein or palm print are extracted from the mosaic images. Such entities are associated with a new unrelated variable termed principal components are transferred via an orthogonal conversion of PCA. These elements have a linear relationship with the original data. The total number of variables in the original data is frequently smaller than the total number of the primary ingredients. A transformation method is used to apply PCA to the extracted entities in order to produce a reduction in the dimensions of the data being extracted. The data vector X={x1, x2, x3, …, xn} is transformed from higher space RM to lower space RK using the transformation W, where n is the total number of samples and Xi is the i^{th} sample. All samples are in the RM dimension.

4.5. Classifiers

Following the extraction of feature data, a collection of classifiers must be trained to predict the class of a particular data point. As a result, when the data class is established, the matching and, as a result, the identity of the biometric modalities under consideration are established. In the following section, the classifiers employed in the proposed system are discussed.

4.5.1. K-nearest neighbors

a. Linear *k*-NN

Because it stores all data points, linear *k*-NN is regarded as a sluggish learning method. The assessment of similarity can be used to categorize the batch of data. In most cases, linear *k*-NN operates by allocating new patterns to the data nearest *k* neighbors. The indicated data distribution is not postulated by *k*-NN.

b. Weighted *k*-NN

Dudani [30] introduced the weighted *k*-NN rule. Data points in a plane are sketched, the nearest neighbors to points that appear to be gathered are assigned to different weights using the distance-weighted function, the adjacent neighbors are assigned to the intensive weight of 1 and the farther ones are assigned to weight 0. The other neighbors are assigned to interstice weights scaled between the adjacent and farther ones.

For the k number of observations let wi be the weights of x1, x2, …, xk. and y1, y2, …, yk are the classified classes. Then the classified result is as:

$$\hat{y} = \arg max_y \sum_{i=1}^{k} \begin{cases} w_i, & if\ c(x_i) = yi \\ 0, & otherwise \end{cases} \tag{2}$$

where $\hat{y}$ is the vector of nearest neighbors, c(xi) is the ith class label.

4.5.2. Support vector machine (linear and non-linear)

Classification was the major purpose of SVM. SVMs were then used to achieve rank learning and regression analysis. SVM develops a nonlinear mapping function as an effort to represent the entering data in the feature space in order to obtain a linearly separable regression of the input space. SVM is used in this proposal to anticipate the data's behavior.

5. RESULTS AND DISCUSSION

A set of classifiers are supplied with data derived from the feature extraction algorithm on hand-vein and palm-print modalities using the Log-Gabor filter. The following steps are employed to conduct the experiments. To begin with, PCA is employed to reduce the dimensionality of the data obtained from the Log-Gabor filter. Second, the linear and weighted *k*-NN classifiers, as well as the linear and non-linear SVM classifiers, are trained for each modality individually. And finally, the same classifiers are applied to fused modalities at the sensor level. The precision and recall performance of the classifiers were measured using accuracy and F-measure. These terms can be summed up in a few words.

– Precision/ positive predictive amount. Precision is one of the major metrics that can be applied to space samples. Precision is actually an illustration of random errors that may occur in pattern classification. Precision is the fraction of convenient instances of the returned instance.

$$Precision = \frac{t_p}{t_p + f_p} \tag{3}$$

where t_p stands for true positive and *fp* is false positive. The proportion of convenient instances that have returned out of the entire number of linked instances is known as recall/sensitivity.

$$Recall = \frac{t_p}{t_p + f_n} \tag{4}$$

where t_p is stand for true positive and *fn* is false negative.

– Accuracy depicts a combination of both random and systematic observational mistakes. The discrepancy between an outcome and an appropriate value is known as systematic error. As a result, great precision, and trueness result in high accuracy.

$$Accuracy = \frac{t_p + t_n}{t_p + t_n + f_n + f_p} \tag{5}$$

where t_p is stand for true positive, t_n is true negative, and *fn* is false negative and *fp* is false positive.

– F-measure (F1 score or F-score): In binary classification, F-measure is a key metric in order to determine the accuracy of test results. Therefore, F-measure offers an accurate measurement of the test's precision. It is also considered the harmonic average of recall and accuracy.

$$F - measure = 2\,\frac{Precision.Recall}{Precision + Recall} \tag{6}$$

5.1. One modality with different classifier

The next stage is to assess how well each classifier performed when used with the various modalities once classifiers have been developed for each one. Both hand vein and palm prints are subject to the accuracy measurements. As the suggested strategy necessitates the use of such modalities in sensor-level recognition.

5.1.1. Hand-vein

Table 1 highlights the research from the single-mode biometric hand-veining with a variety of classifiers. By examining the results of various classifiers linked with hand-vein, it is clear that linear *k*-NN has the best performance rate with an accuracy of 65.66 and an F-measure rate of 0.6596. The weighted *k*-NN has the second highest value, which is close to the linear *k*-NN's outcome. The non-linear SVM has the lowest performance value among the four classifiers, with an accuracy of 61.80 and an F-measure of 0.6195.

Table 1. Different classifier performance for the hand-vein

Classifier	Accuracy (%)	Recall	Precision	F-measure
Linear *k*-NN	65.66	0.6566	0.6596	0.6596
Weighted *k*-NN	64.95	0.6495	0.6435	0.6460
Linear SVM	64.98	0.6498	0.6490	0.6480
Non-Linear SVM	61.80	0.6180	0.6198	0.6195

5.1.2. Palm-print

The results obtained from the evaluation of the palm-print modality biometric with different classifiers are tabulated in Table 2. By analyzing the tabulated data, the non-linear SVM had the greatest performance accuracy value of (87.80) and an F-measure of (0.879) when using different classifiers for the palm-print modality, while the weighted *k*-NN had the worst performance accuracy value of (85.45) and an F-measure of (0.8503) among the four classifiers.

From the preceding two tables, because of the disparity between the highest value obtained for the hand-vein using linear *k*-NN where the accuracy rate was (65.66) and the F-measure was (0.6596), and the highest value obtained by Palm-Print using the non-linear SVM which has a performance rate of accuracy (89.73) and an F-measure of (0.8930), it can be seen that palm-print outperforms the hand-vein for all the classifiers values. The outcome of the fused modalities at the sensor level will be examined next, with the assurance that the palm-print has more characteristics than the fingerprint.

Table 2. Performance of different classifier for the palm-print

Classifier	Accuracy (%)	Recall	Precision	F-measure
Linear *k*-NN	89.23	0.8822	0.8834	0.8832
Weighted *k*-NN	86.54	0.8597	0.8620	0.8603
Linear SVM	89.30	0.8933	0.8910	0.8909
Non-Linear SVM	89.73	0.8925	0.8964	0.8930

5.2 Fused modalities with different classifiers

The results acquired when fusing the two modality biometrics at the sensor level are depicted in Table 3. When looking at the tabulated data, it's clear that the performance of different classifiers on the fused modality at the sensor level has increased significantly. In comparison to the previous classifiers on the individual modalities, the non-linear SVM has the best performance among them. The non-linear SVM classifier has achieved an accuracy of (94.12) and an F-measure of (0.9425). On the other hand, the weighted *k*-NN, which has an accuracy of (90.32) and an F-measure of (0.8914), has achieved the worst performance among the classifiers on the fused modalities. Please recall that the same classifier had a performance accuracy of (86.54) and an F-measure of (0.8603) in the palm-print modality, and a performance accuracy of (64.95) and an F-measure of (0.6460) in the hand-vein case, as shown in Table 2, which also show a substantial improvement over singly modalities even in its worst cases. As a result, sensor level fusion of two modalities shows a significant performance gain over a single modality.

Table 3. Performance of different classifiers for the fused modality

Classifier	Accuracy (%)	Recall	Precision	F-measure
Linear *k*-NN	92.13	0.920	0.9212	0.9215
Weighted *k*-NN	90.32	0.9010	0.8932	0.8914
Linear SVM	92.02	0.9202	0.9104	0.9136
Non-Linear SVM	94.12	0.9415	0.9412	0.9425

5.3. Memory usage

The suggested system performs matching on the fused image rather than separate images during sensor level fusion, necessitating just the fused image to be saved throughout the registration stage. In this case, the storage size will be more than 50% smaller than the size of individual photos. Consequently, the amount of memory needed to store such photos has been lowered. One must recall that the amount of memory is determined by the number of modalities fused.

6. CONCLUSION

By examining the experimental findings and observations, it is possible to conclude that the performance gained by fusing two modalities at the sensor level with a nonlinear SVM is superior to that achieved by utilizing a single modality. When employing Palmprint or Hand-vein, the fused modalities' overall performance is better than the best single modality performance previously reported in the literature. The comparison can be noticed when all classifier values are considered. When comparing the worst cases of performances of the proposed system and the systems that use single features, the proposed system has achieved a 4 percent accuracy gain over the system that utilizes the single feature, Palmprint. Likewise, the proposed system also achieved more than 33% of accuracy when compared to the single-feature system, hand-vein.

Furthermore, fusing images takes much less disk space. The amount of memory needed to store the images is determined by the number of modalities that will be integrated. Image storage requirements for two modalities will be decreased by more than half when compared to storing the two modality images separately.

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