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Online Person Identification based on Multitask Learning

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Abstract: In the digital world, everything is digitized and data are generated consecutively over the times. To deal with this situation, incremental learning plays an important role. One of the important applications that needs an incremental learning is person identification. On the other hand, password and code are no longer the only way to prevent the unauthorized person to access the information and it tends to be forgotten. Therefore, biometric characteristics system is introduced to solve the problems. However, recognition based on single biometric may not be effective, thus, multitask learning is needed. To solve the problems, incremental learning is applied for person identification based on multitask learning. Considering that the complete data is not possible to be collected at one time, online learning is adopted to update the system accordingly. Linear Discriminant Analysis (LDA) is used to create a feature space while Incremental LDA (ILDA) is adopted to update LDA. Through multitask learning, not only human faces are trained, but fingerprint images are trained in order to improve the performance. The performance of the system is evaluated by using 50 datasets which includes both male and female datasets. Experimental results demonstrate that the learning time of ILDA is faster than LDA. Apart from that, the learning accuracies are evaluated by using K-Nearest Neighbor (KNN) and achieve more than 80% for most of the simulation results. In the future, the system is suggested to be improved by using better sensor for all the biometrics. Other than that, incremental feature extraction is improved to deal with some other online learning problems.

Keywords: Feature extraction, biometrics, Linear Discriminant Analysis (LDA), incremental learning, multitask learning, person identification

1. Introduction

In the era of globalization, life has become convenient when people are using modern technologies such as smart phones, computers and others to do various activities. Online financial transactions, cashless payment and smart home systems are some of the applications resulted from the technology advancement [1-6]. These technologies continuously produce large data stream [7]. Traditional approaches are not able to deal with this condition effectively in terms of performance and accuracy. Therefore, it is very important to have a method that can handle the data whenever data are available. This kind of learning is called "Online" or "Incremental Learning" [8-9]. Incremental learning is very important in many applications considering that the data are not always available at the early stage [10-14]. One of the important applications is person identification because the faces could be changed due to aging, lighting, make up and etc.

Person identification can be easily hacked if the security is not strong enough. Thus, security become a top concern. Most of the conventional person identification are using password-based security where forces user to

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remember username and password combinations [15]. Nevertheless, password authentication may fail when it is not addressed seriously. Username and password are also easily shared, misused and it also can be stolen [16]. Hence, a more secure form of authentication is needed. Consequently, biometric security is becoming increasingly popular to protect the data from the intruder. Biometric system is a technological system that identify the person by recognizing their characters such as their face, fingerprint, iris, voice, and so forth. Most of the person identification system consider only single characteristic for the recognition purposes. This learning is called single task learning. It may not be sufficiently robust due to some limitation such as noisy data and spoof attack [16].

In order to solve the above-mentioned problems, incremental learning method is applied to person identification based on multitask learning. Multitask learning uses more than one characteristic for the recognition [17] [18]. For person identification, feature extraction is crucial in image recognition. There are two popular feature extraction techniques namely, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). In this paper, LDA is chosen because it is a supervised technique and it provide a good separation of the classes. LDA is then updated incrementally using ILDA. To improve the performance, face and fingerprint biometric characteristics is chosen for the multitask learning. Face feature is chosen because the face recognition is the most exciting biometric features and more accurate way for the person identification system. Apart from that, fingerprint is chosen to be one of the features because of their uniqueness and consistency over- time. The fingerprint is the form of the tiny ridges and the arrangement of the structure of the ridges. The performance of the person identification is evaluated based on KNN approach.

The remainder of this paper is organized as follows: Section 2 provides a quick review of LDA and ILDA. Section 3 introduces the methodology. Section 4 shows the experimental results. Finally, Section 5 offers the conclusions and future works.

2. Illustrations

2.1 Batch Linear Discriminant Analysis (LDA)

LDA is a well-known technique for dimensionality reduction and classification [9]. LDA is widely used in statistics, machine learning and pattern recognition to find a linear combination of features which characterizes or separates two or more objects. Thus, LDA is a very practical tool for classification and dimensionality reduction [18]. The optimal projection or transformation in classical LDA is obtained by minimizing the within-class distance $\boldsymbol{S}_w$ and maximizing the between-class distance simultaneously $\boldsymbol{S}_b$ thus achieving maximum class discrimination $J(\boldsymbol{w})$ [9] [18-21]. In this way, vectors that maximally separates the classes in the feature space is obtained. Between-class and within-class distance are shown in (1) and (2) [9] [18] [21-22].

$$\boldsymbol{S}_w = \sum_{c=1}^{C}\sum_{i=1}^{n_c}\left(\boldsymbol{\mu}_{ci} - \overline{\boldsymbol{\mu}}_c\right)\left(\boldsymbol{\mu}_{ci} - \overline{\boldsymbol{\mu}}_c\right)^T \tag{1}$$

$$\boldsymbol{S}_b = \sum_{c=1}^{C} n_c\left(\overline{\boldsymbol{\mu}}_c - \overline{\boldsymbol{\mu}}\right)\left(\overline{\boldsymbol{\mu}}_c - \overline{\boldsymbol{\mu}}\right)^T \tag{2}$$

while maximum class discrimination $J(\mathbf{w})$ is defined in (3)

$$J(\boldsymbol{w}) = \frac{\boldsymbol{w}^T \boldsymbol{S}_b \boldsymbol{w}}{\boldsymbol{w}^T \boldsymbol{S}_w \boldsymbol{w}} \tag{3}$$

Here, $\overline{\boldsymbol{\mu}}_c$ is a mean of the class and $\overline{\boldsymbol{\mu}}$ is a mean of overall data. In this way, we can get the vectors that maximally separates the classes in the feature space.

2.2 Incremental Linear Discriminant Analysis (ILDA)

In the real situations, data are not always available at the beginning. Thus, LDA may not perform well when the new data is received. In ILDA, discriminant space model is updated incrementally when new data is given, which mean that the within-class distance and between-class distance are updated incrementally with new data by (4) and (5)[9][18][20-22].

$$\boldsymbol{S}'_w = \sum_{c=1}^{C'} \left(\sum_{i=1}^{n_c} \left(\boldsymbol{\mu}_{ci} - \overline{\boldsymbol{\mu}}'_c\right)\left(\boldsymbol{\mu}_{ci} - \overline{\boldsymbol{\mu}}'_c\right)^T + \sum_{i=1}^{k_c} \left(\boldsymbol{\alpha}_{ci} - \overline{\boldsymbol{\mu}}'_c\right)\left(\boldsymbol{\alpha}_{ci} - \overline{\boldsymbol{\mu}}'_c\right)^T \right) \quad (4)$$

$$\boldsymbol{S}'_b = \sum_{c=1}^{C} n'_c \left(\overline{\boldsymbol{\mu}}'_c - \overline{\boldsymbol{\mu}}'\right)\left(\overline{\boldsymbol{\mu}}'_c - \overline{\boldsymbol{\mu}}'\right)^T \quad (5)$$

where $n'_c = n_c + k_c$ and $\overline{\boldsymbol{\mu}}'_c$ is a new mean for the particular class while $\overline{\boldsymbol{\mu}}'$ is a new mean for all data.

3. Incremental Linear Discriminant Analysis (ILDA)

Person identification consists of three main stages. The first stage is face recognition while the second stage is fingerprint recognition and the two characteristics are combined into the same domain in the final stage to perform the decision making. Image enhancement, feature extraction and decision making is applied to both face and fingerprint recognition as shown in figure 1.

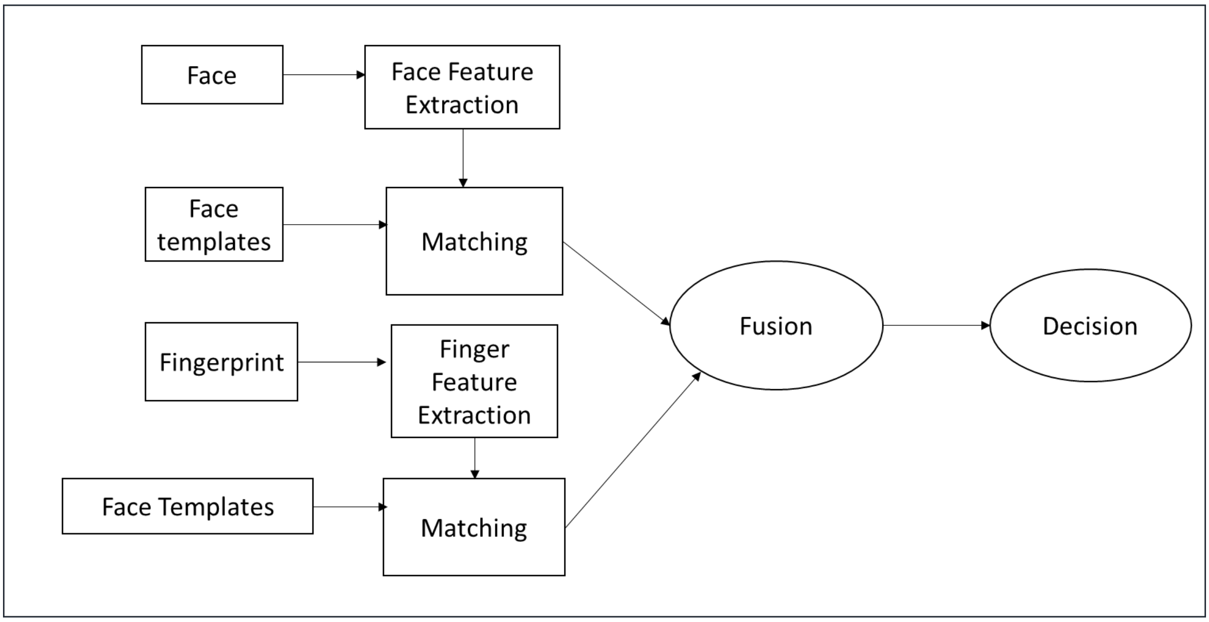

Fig. 1 - Multitask biometric system block diagram

The datasets of 50 persons for both male and female are obtained manually. Ten pictures of each person are taken with difference angle, background and lighting conditions. Ten fingerprints for each one of them are also obtained using printer's scanner. In the pre-processing part, face and fingerprint images are converted from Red Green Blue (RGB) to grayscale image as shown in Figure 2 and Figure 3.

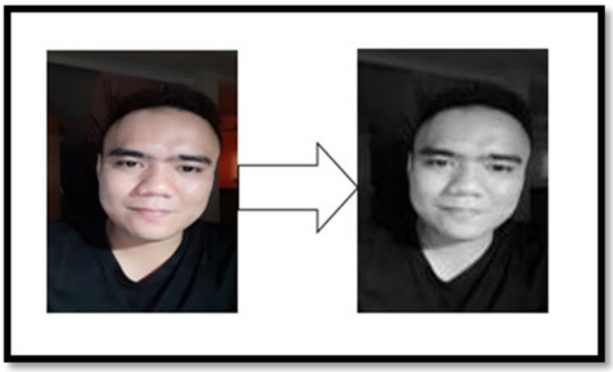

Fig. 2 - Conversion from RGB to grayscale image for face

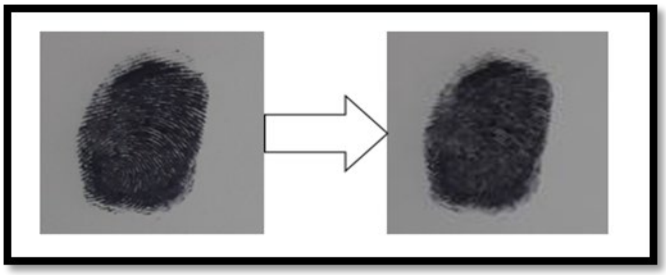

Fig. 3 - Conversion from RGB to grayscale image for fingerprint

It is important to convert the image to grayscale image for better image processing. These datasets then divided into 60% training set and 40% testing data. At the beginning, LDA is applied to the initial data and initial feature space is constructed. The remaining data are given one by one to update the feature space by ILDA. The recognition accuracy is done by using KNN classifier. This algorithm is used to classify the object based on their templates in the database [23]. KNN is fast and simpler compare to the other methods. The Euclidean distance matrix is used to calculate the distance between two data points. The equation for the Euclidean distance is shown in (6) [24].

$$d(x, y) = \sqrt{(x_1 - y_1)\ldots\ldots(x_n - y_n)} \tag{6}$$

where x and y is different two different data points.

The whole program is developed using Matlab R2018b while the technical specifications of the device are shown as follow:

1. ASUS A450C Notebook.
2. Processor of Intel Core i5-3337U 1.80 Ghz core X2.
3. 6GB DDR3 (RAM).
4. Intel Graphic 4000 + Nvidia Geforce GT 720M 2GB memory.
5. 750GB (hardisk).

The general process of the person identification is shown in Fig. 4.

4. Results and Discussion

In this section, the performance of person identification is carried out with LDA and ILDA. The learning time and recognition accuracy is carried out with face and fingerprint datasets. As seen in Fig. 5 and Fig. 6, the learning time for ILDA is much faster compared to LDA. Both algorithms are executed in the MATLAB program. This is because LDA is a batch mode learning where the whole data need to be retrained when the new data is given. On the contrary, ILDA only update the feature space when the new data is given. The data is discarded after the training for ILDA.

To further evaluate the performance of LDA and ILDA, the learning time are obtained by varying the number of dataset for both biometric datasets. Table 1 shows that the learning time for ILDA is faster compared to LDA even though the datasets are increasing. The learning time is increased as the number of data are increasing for both LDA and ILDA. This is a normal condition where the system needs more time to update the feature space for LDA and ILDA when the data are increased.

Next, the recognition accuracies for both LDA and ILDA are shown in Table 2. The results are obtained by using 50 datasets for both biometric characteristics. As seen in Table 2, the results obtained shows that ILDA achieves higher recognition accuracies compared to LDA.

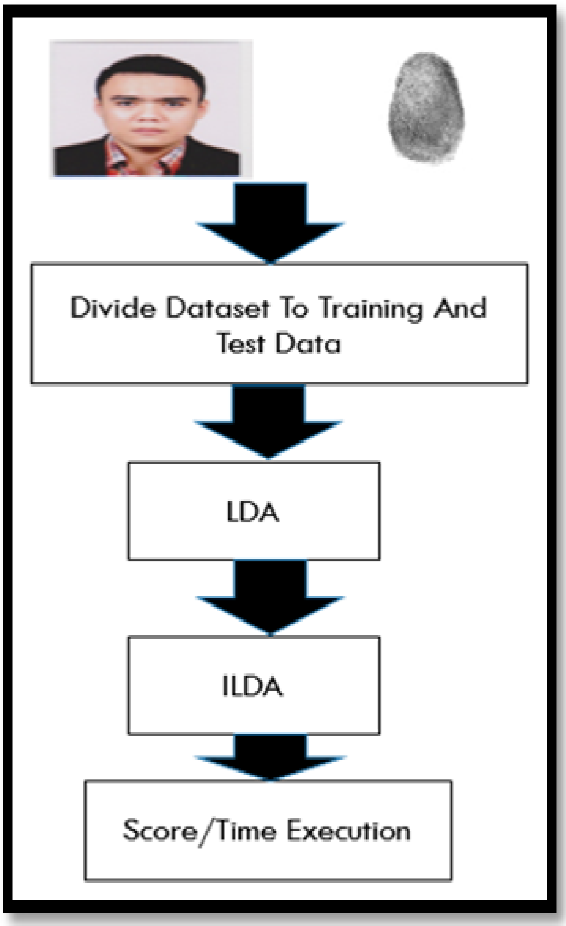

Fig. 4 - Overall person identification system

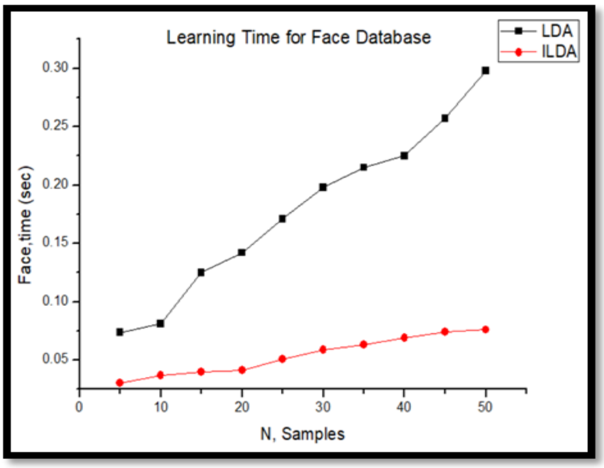

Fig. 5 - Learning time for face

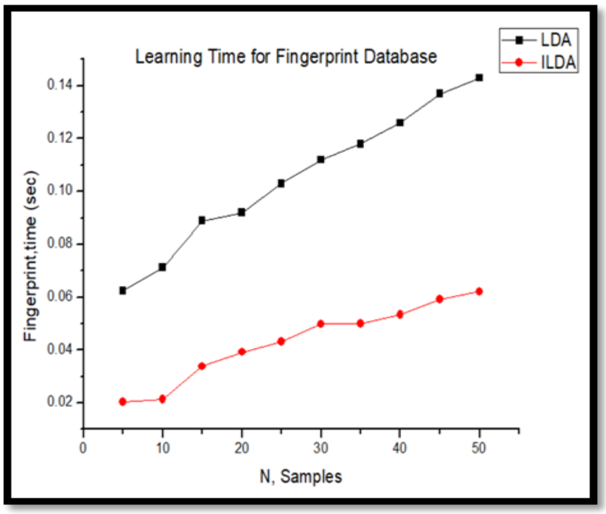

Fig. 6 - Learning time for fingerprint

Table 1 - Learning time for LDA and ILDA

N, Samples	Face, Time(seconds)		Fingerprint, Time(seconds)	
	LDA	**ILDA**	**LDA**	**ILDA**
5	0.0737	0.0305	0.0625	0.0203
10	0.0812	0.0368	0.0712	0.0214
15	0.125	0.0398	0.0889	0.0338
20	0.142	0.0413	0.092	0.0392
25	0.171	0.051	0.103	0.0432
30	0.198	0.059	0.112	0.0498
35	0.215	0.0632	0.118	0.0501
40	0.225	0.069	0.126	0.0535
45	0.257	0.074	0.137	0.0591
50	0.298	0.076	0.143	0.0621

The main reason is that memory storage is required for LDA. The new data need to be stored together with previous data in the memory. When the system contained a lot of the information, this will cause the degradation of performance. The learning time is increased when the memory storage is increased [12]. Therefore, it is concluding that ILDA perform faster compare to LDA without affect the recognition accuracies.

Table 2 - Recognition accuracies for LDA and ILDA

	Face Accuracy (%)		**Fingerprint Accuracy (%)**	
N, data	**LDA**	**ILDA**	**LDA**	**ILDA**
50	83.4	86.1	88.2	89.5

5. Conclusions and Future Works

As a conclusion, ILDA is adopted in the feature extraction part for incremental person identification. From the experimental results, the performance of ILDA is better than traditional LDA. In addition, the recognition accuracies of ILDA are superior to LDA even though the datasets are increasing. Besides, multitask learning based on face and fingerprint is adopted for person identification. The reason why multitask learning is adopted because the performance of the system based on single task might not optimistic. In the future, other biometrics characteristics such as iris and voice will be considered to be included in the system. Apart from that, Convolution Neural Network (CNN) will be also considered to be adopted as a classifier in order to improve the accuracies [25] [26]. ILDA is suggested to be improved to deal with other online learning problems. Besides, person identification based on biometric characteristics can be included to replace QR code for the attendance record.

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