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RFID Tag Protection using Face Feature

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ABSTRACT

Radio Frequency Identification (RFID) is a common term for technologies using micro chips that are able to communicate over short-range radio and that can be used for identifying physical objects. RFID technology already has several application areas and more are being envisioned all the time. While it has the potential of becoming a really ubiquitous part of the information society over time, there are many security and privacy concerns related to RFID that need to be solved. This paper proposes a method which could protect private information and ensure RFID's identification effectively storing face feature information on RFID tag. This method improved linear discriminant analysis has reduced the dimension of feature information which has large size of data. Therefore, face feature information can be stored in small memory field of RFID tag. The proposed algorithm in comparison with other previous methods shows better stability and elevated detection rate and also can be applied to the entrance control management system, digital identification card and others.

Key Words : RFID, Biometric, Face Recognition, LDA

1. INTRODUCTION

Radio Frequency Identification (RFID) technology has gained a foothold as an advanced barcode replacement, a wireless smartcard, and a generic system for attaching automatically readable data to objects. Currently RFID is being used for tracking goods in supply chains, identifying vehicles in toll collection, tracking animals and storing biometric data in electronic passports. In the near future RFID tags might be commonly found on all items sold in stores and even as implants in human bodies[1, 2, 3].

Two major factors in the fast adoption of this technology that recently has taken place have been the decreasing cost and shrinking size of RFID capable devices. Another factor that has contributed to the success of RFID is its suitability to a vast number of applications.

However RFID tags has a problem that the identification information they hold can be used for purposes that violate a user's privacy. A person might be carrying tags for instance in clothes, medicines, books, bank notes, passports and other belongings, and if no protection mechanisms are employed, the data in these tags can be interrogated (or eavesdropped) by any reader, legitimate or not, in the physical proximity of that person. Furthermore, the data is read in clandestine way, so that the user isn't necessarily aware of when and where it happens. This information can then be used, for example, for unauthorized tracking or inventorying purposes [4, 5].

This paper proposes a method which could protect private information and ensure RFID's identification effectively storing face feature information on RFID tag. This method which is improved linear discriminant analysis has reduced dimension of feature information which has large size of data. Therefore, face feature information can be stored in small memory field of RFID tag.

2. RFID SYSTEM

RFID provides a quick, flexible and reliable way to

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electronically detect, track and control various items. RFID systems use radio transmissions to send energy to a transponder (or RFID tag) which in turn emits a unique identification code back to data collection reader (or Interrogator) linked to an information management system. RFID systems effectively utilize two separate antennas one on the transponder and the other one on the reader to accomplish the task of data transfer by radio signals back to the data management system. The data collected from the transponder can be sent either directly to a host computer through standard interfaces, or it can be stored in a portable reader and up-loaded later to a computer for data processing[1].

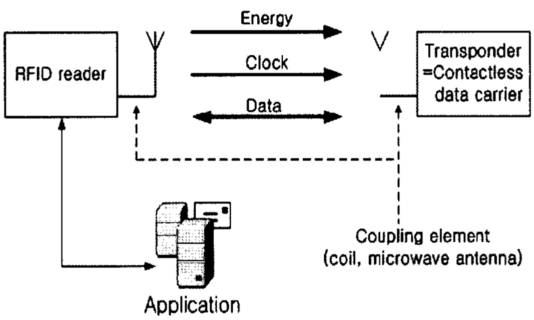

Fig. 1. The reader and transponder are the main components of every RFID system.

Fig. 1 consists of two main components: A RFID reader with one or more attached antennas and a RFID tag. The reader uses RF signals to transfer information and power to tags. Basically, if a tag receives some command from a reader, the tag responds to the reader in the reader's field of view. Tags have memories in its own and the memories have the unique identification number(Serial number) and other information. The integration of several additional components is required to effectively exploit the RFID technology. These components are the controller, sensors, annuciators, actuators, and connectivity to back end business systems. The reader is responsible for transmitting and receiving signals in a defined target environment. The originating signal in the form of an electromagnetic field is utilized (in a passive environment) by the RFID tag. The tag uses the signal to activate and generate a modulated wave, which is the corresponding analog signal. This signals transmitted by the RFID tag which is used during the interrogation by the reader's antenna. The information that was received by the antenna is then processed by the reader and converted into a digital form. This data stream is forwarded to the controller for additional processing[1, 3].

3. FACE RECOGNITION

3.1. PCA(Principal Component Analysis)

Face recognition has a wide range of applications, such as face-based video indexing and browsing engines, biometric identity authentication, human computer interaction, and multimedia monitoring/surveillance [6]. Within the past two decades, numerous face recognition algorithms have been proposed, and detailed surveys of the developments in the area have appeared in the literature [7, 8]. Feature extraction is one of the most fundamental problems in face recognition [9]. PCA is a popular feature extraction and dimension reduction technique for face recognition.

PCA can be used to approximate the original data with lower dimensional feature vectors. The basic approach is to compute the eigenvectors of the covariance matrix of the original data, and approximate it by a linear combination of the leading eigenvectors[7, 8].

By using PCA procedure, the test image can be identified by first, projecting the image onto the eigenface space to obtain the corresponding set of weights, and then comparing with the set of weights of the faces in the training set. The distance measure used in the matching could be a simple Euclidean, or a weighted Euclidean distance. The problem of low-dimensional feature representation can be stated as follows [10, 11]:

Let $X=(x_1, x_2, \cdots, x_N)$ represents the $N \times M$ data matrix, where each x_i is a face vector of dimension N, concatenated from a $n \times m$ face image. Here n represents the total number of pixels ($n \times m$) in the face image and N is the number of face images in the training set. The PCA can be considered as a linear transformation by equation (1) from the original image vector to a projection feature vector, i.e.

$$Y = W^T X \quad (1)$$

where Y is the $N \times M$ feature vector matrix, m is the dimension of the feature vector, and transformation matrix W is an $N \times M$ transformation matrix whose columns are the eigenvectors corresponding to the m largest eigenvalues computed according to the formula (2):

$$\lambda e_i = S e_i \quad (2)$$

Here the total scatters matrix S and the mean image of all samples are defined as

$$S = \sum_{i=1}^{N} (x_i - \mu)(x_i - \mu)^T,\ \mu = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (3)$$

After applying the linear transformation W_T, the scatter of the transformed feature vectors $\{y_1, y_2, \cdots, y_N\}$ is $W^T SW$. In PCA, the projection W_{opt} is chosen to maximize the determinant of the total scatter matrix of the projected samples, i.e.,

$$W_{opt} = \arg\max_{W} |W^T SW| = [w_1, w_2, \ldots, w_m] \quad (4)$$

where $\{w_i | i = 1, 2, \cdots, m\}$ is the set of n-dimensional eigenvectors of S corresponding to the m largest eigenvalues. In other words, the input vector (face) in an n-dimensional space is reduced to a feature vector in an m-dimensional subspace. The dimension of the reduced feature vector m is much less than the dimension of the input face vector n.

3.2. LDA (Linear Discriminant Analysis)

It determines a set of projection vectors maximizing the between-class scatter matrix (S_B) and minimizing the within-class scatter matrix (S_W) in the projective feature space[12, 13].

Some assumptions and definitions in mathematics are provided at first. Let denotes the dimension of the original sample space, and is the number of classes [14]. The between-class scatter matrix and the within-class scatter are defined as below:

$$S_W = \sum_{i=1}^{c} \sum_{x_k \in X_i} (x_k - \mu_i)(x_k - \mu_i)^T = \Phi_W \Phi_W^T \quad (5)$$

$$S_B = \sum_{i=1}^{c} N_i (\mu_i - \mu)(\mu_i - \mu)^T = \Phi_B \Phi_B^T \quad (6)$$

where N_i is the number of samples in class C_i ($i = 1, 2, \cdots, c$), N is the number of all the samples, μ_i is the mean of the samples in the class C_i, and μ is the mean of all the samples. The total scatter matrix i.e. the covariance matrix of all the samples is defined as:

$$S_T = S_B + S_W = \sum_{i=1}^{N} (x_i - \mu)(x_i - \mu)^T = \Phi_T \Phi_T^T \quad (7)$$

LDA tries to find an optimal projection: $W = [w_1, w_2, \cdots, w_{c-1}]$, which satisfies

$$J(W) = \arg\max_{W} \frac{|W^T S_B W|}{|W^T S_W W|} \quad (8)$$

As well known, W can be constructed by the eigenvectors of $S_W^{-1} S_B$. But this method is numerically unstable because it involves the direct inversion of a likely high-dimensional matrix. The most frequently used LDA algorithm in practice is based on simultaneous diagonalization. The basic idea of the algorithm is to find a matrix W that can simultaneously diagonalize both S_W and S_B, i.e.,

$$W^T S_W W = I,\ W^T S_W W = \Lambda \quad (9)$$

Most algorithms require that S_W be non-singular, because the algorithm diagonalize S_W first. The above procedure will break down when S_W is singular. It surely happens when the number of training samples is smaller than the dimension of the sample vector. An available solution to the singularity problem is to perform PCA before LDA, which greatly reduces the dimension of both S_W and S_B. Yet the PCA step essentially removes null space from both S_W and S_B. Therefore, this step potentially loses useful information.

3.3. Proposed Method

LDA often suffers from the small sample size problem in face recognition tasks, when dealing with the high dimensional face data. So, this paper proposes an approach using improved LDA to effectively avoid this loss of discriminative information in face recognition.

The between-class scatter matrix which is of size $N \times N$ can be expressed as $S_B = \Phi_B \Phi_B^T$ where $\Phi_B = [\sqrt{n_i}(\mu_1 - \mu), \ldots, \sqrt{n_C}(\mu_C - \mu)]$, N is the dimensionality of the samples, n_i is the number of samples of i-

th class, μ_i is the mean vector of *i-th* class, μ is the total mean vector of all samples, and C is the number of classes. Proposed method finds the eigenvectors of $S_B = \Phi_B\Phi_B^T$ which can be derived from the eigenvectors of the matrix, $\Phi_B\Phi_B^T$ of size C. Let λ_i and e_i be the *i-th* eigenvalue and its corresponding eigenvector of $\Phi_B\Phi_B^T$, where $i = 1, 2, \cdots, C$, and let λ_i be sorted in the decreasing order of magnitude. Since $(\Phi_B\Phi_B^T)(\Phi_B e_i) = \lambda_i \Phi_B e_i$, $y = \Phi_B e_i$ is the eigenvector of S_B. As the rank, m of S_B satisfies $m = rank(S_B) = \min(N, C-1)$, there is no discriminative information in the null space of S_B. The first m eigenvectors, $Y = [y_1, y_2, \cdots, y_m] = \Phi_B E_m$, whose corresponding eigenvalues are greater than 0, are used, where $E_B = [e_1, e_2, \cdots, e_m]$.

Let $D_B = diag[\lambda_1, \lambda_2, \cdots, \lambda_m]$, and further let $Z = YD_B^{-\frac{1}{2}}$ denote a projection matrix. Projecting S_W into the subspace spanned by Z, the result of equation is following as:

$$\tilde{S}_W = Z^T S_W Z \tag{10}$$

Let u_i be the *i-th* eigenvector of $\tilde{S}_W$, where $i = 1, 2, \cdots, m$, corresponds to the *i-th* eigenvalue λ_i'. The diagonal matrix of eigenvalues is denoted as $D_W = diag[\lambda_1', \lambda_2', \cdots, \lambda_m']$, which corresponds to the matrix, U of eigenvectors of $\tilde{S}_W$.

Let $P = ZU$ and further let $Q = PD_W^{-\frac{1}{2}}$ be a projection matrix. Projecting S_T and S_W into the subspace spanned by Q, the result of equation is following as:

$$Q^T S_W Q = I \tag{11}$$

$$Q^T S_T Q = \tilde{S}_T \tag{12}$$

In order to maximize formula (8), we need only to select the eigenvectors of $\tilde{S}_T$. Let us denote the selected eigenvectors as $V = [v_1, v_2, \cdots, v_m]$, the corresponding diagonal matrix of eigenvalues as D_T. Note that D_T is an $m' \times m'$ diagonal matrix. The optimal discriminant feature extractor can be derived through $A = V^T Q^T$.

4. EXPERIMENTAL RESULTS

The proposed algorithm is adopted to extract the features of human face images for face recognition. In order to test the performance of the proposed algorithm in this paper, the features of face images are extracted by previous methods and the proposed method respectively.

The Olivetti Research Lab (ORL) face database contains 40 distinct subjects, each subject having ten different images, taken in different conditions. Four images per subject are chosen as training samples, the remaining six images are treated as test samples.

Table 1. Experimental Results

Method		Rate (%)
PCA	ORL Database	86.2
	Yale Database	82
PCA+LDA	ORL Database	88
	Yale Database	84.7
Proposed Method	ORL Database	93
	Yale Database	89

Table 1 shows comparisons of performance by proposed algorithm for two face databases which are ORL face database and Yale University face database[15, 16]. The results of the experiments show that the present method is more efficient than previous methods that are applied to PCA or PCA+LDA in terms of classification accuracy.

5. CONCLUSION

This paper develops a novel improved linear discriminant analysis method, which draws on a variant of discriminant analysis criterion and exploits the strength of proposed LDA algorithm. The proposed method can solve the small sample size problem without the loss of useful information and reduce dimension to decrease feature data size. Therefore it is suitable for protecting private information and ensuring RFID's identification. Furthermore it can be treated as a unified algorithm of PCA+LDA. The effectiveness of the new method has been demonstrated through experiments on ORL face databases and Yale University face database. In future, this method can be intended to develop a nonlinear version of the algorithm.

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REFERENCE

1. K. Finkenzeller, *RFID Handbook: Fundamentals and Applications in Contactless Smart Cards and Identification*, John wiley & Sons, Ltd. 2003.
2. RFID journal, H.K. Launches RFID Supply Chain Project, June 2005.
3. Weinstein, R. "RFID: a technical overview and its application to the enterprise", IT Professional Volume 7, Issue 3, May-June 2005 Page(s):27 - 33 Digital Object Identifier 10.1109/MITP.2005.69
4. DoD, Final Regulatory Flexibility Analysis of Passive Radio Frequency Identification, June 2003.
5. Sarma, S. et al.: *RFID Systems and Security and Privacy Implication*, Workshop on Cryptographic Hardware and Embeded Systems, pp.454-470, LNCS, 2002.
6. R. Chellappa, C. L.Wilson, and S. Sirohey, "Human and machine recognition of faces: A survey," Proc. IEEE, vol. 83, pp. 705–740, May 1995.
7. M. Turk, "A random walk through eigenspace," IEICE Trans. Inform. Syst., vol. E84-D, pp. 1586-1695, Dec. 2001.
8. Shaogang Gong, Stephen J McKenna, and Alexandra Psarrou, *Dynamic Vision From Images to Face Recognition*, Imperial College Press, World Scientific Publishing, May 2000.
9. X.J Wu, J.Y. Yang, S.T. Wang, et al., "A new algorithm for solving optimal discriminant vectors", Journal of Computer Science and Technology, vol.19, no.3, pp.324~330, 2002.
10. G. L. Marcialis and F. Roli, "Fusion of appearance-based face recognition algorithms," Pattern Analysis & Applications, Vol.7. No. 2, pp. 151-163, Springer-Verlag, London, 2004.
11. A. M. Martinez and A. C. Kak, "PCA versus LDA," IEEE Trans. On pattern Analysis and Machine Intelligence, Vol. 23, No. 2, pp. 228-233, 2001.
12. P. N. Belhumeur, J. Hespanda, and D. Kiregeman, "Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection," IEEE Trans. on PAMI, Vol. 19, No. 7, pp. 711-720, July 1997.
13. W. Zhao, R. Chellappa, A. Rosenfeld, and P. J. Phillips, "Face recognition: A literature survey," ACM Comput. Surveys, pp. 399–458, 2003.
14. Wang, X., and Tang, X., "Random sampling LDA for face recognition", Proc. of IEEE Conf. on Computer Vision and Pattern Recognition, 2004.
15. http://www.uk.research.att.com
16. http://cvc.yale.edu/projects/yalefaces