A Study of Face Recognition based on Wavelet and LDA Algorithm

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ABSTRACT

Face recognition has been broadly applied in the areas such as biometric identity authentication, access surveillance and human-computer interface. More recently, the technique of face recognition has been markedly extended to the applications of the optimality of human-computer interface due to the promotion of “ intelligent life ”. Additionally, video conference, image content indexing and medical diagnostics are also the most important applications of face recognition. One of the most important topics in face recognition is the extraction and selection of face features, which aims to greatly reduce the higher dimensionality of face space and further to lower the high complexity and heavy loading of the computation of scatter covariance matrices. Face recognition (FR) often encounters the so called “ small sample size ” (SSS) problem resulting from the small number of available training samples compared to the dimensionality of the sample space. Hence, both within-class scatter matrix SW and between-class scatter matrix SB become singular. It implies that the eigensystem computation can be unstable. This is why we would like to propose an algorithm based on wavelet transform and LDA to solve the difficulties concerning the SSS problem and high dimensionality in training samples. This research modifies Fisher ’ s criterion as |?仆SB?戍/|?仆(SW+?庶) ?戍, where ? is the set of generalized eigenvectors of and is usually chosen as a matrix with orthonormal column vectors which maximize the ratio of the determinant of the between-class scatter matrix to that of the within-class scatter matrix. On the other hand, is a very small positive value (i.e., 10-3 in this research), which is added to the diagonal elements of SW to let SW+?庶 be a positive definite matrix. This can help us to solve the difficulties of unstable eigensystem computation. Here, we call this modified method as M-LDA (Modified-LDA). As to Fisher ’ s LDA, we call it as conventional LDA. Another popular method called D-LDA will also be compared. The Olivetti Research Lab (ORL) face database will be adopted in this research. When applying Haar wavelet and taking maximum available feature spaces, the average recognition rate of M-LDA is 91.5% compared to 87.5% of conventional LDA and 82.5% of D-LDA. However, when Daubechies 9/7 wavelet is used, the average recognition rate of M-LDA keeps the same, but conventional LDA and D-LDA slightly decrease to 86.8% and 82.3%, respectively. Especially, when training samples are deficient, e.g., only two training samples, the recognition rate of M-LDA can be still up to 83%, which is superior to 75% of conventional LDA and 61% of D-LDA, respectively. The results also reveal the following two key points: (1) the null space of within-class scatter matrix SW is not useless. Instead, it provides the most significant discriminant information. (2) the recognition rate of D-LDA is far lower than that of M-LDA and conventional LDA especially under less feature spaces. It clearly illustrates that the null space of between-class scatter matrix SB contains the most important discriminative information. Finally, the effect of wavelet transformation on recognition rate is also examined. This research compares the recognition rate of D-LDA proposed here with literature [11] and [26]. We use wavelet to reduce the dimensionality of face spaces as a preprocessing, but literature [11] and [26] do not. The calculated results show that the algorithm of wavelet + M-LDA proposed in this research has a recognition rate of 91%, which is higher when compared to 82.9% of [11], but it is similar to 90.8% of [26]. This research proposes M-LDA algorithm. The results of recognition rate are well compared with that of conventional LDA and D-LDA. The result reveals that M-LDA has a better recognition rate especially under deficient training samples. Moreover, recognition rate can rise with an increase in the number of training samples or face classes. But on the other hand, it also strongly increases the training time of face database.

Keywords : Face Recognition ; Wavelet Transform ; Linear Discriminant Analysis

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