Adaptive Feature and Score Level Fusion Strategy Using Genetic Algorithms

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Abstract—Classifier fusion is considered as one of the best strategies for improving performance of general purpose classification systems. On the other hand, fusion strategy space strongly depends on classifiers, features and data spaces. As the cardinality of this space is exponential, one needs to resort to a heuristic to find a sub-optimal fusion strategy. In this work, we present a new adaptive feature and score level fusion strategy (AFSFS) based on adaptive genetic algorithm. AFSFS tunes itself between feature and matching score level, and improves the final performance over the original on both levels, and as a fusion method, it does not only contain fusion strategy to combine the most relevant features so as to achieve adequate and optimized results, but also has the extensive ability to select the most discriminative features. Experiments are provided on the FRGC database showing that the proposed method produces significantly better results than the baseline fusion methods.

Keywords: classifier fusion, adaptive genetic algorithm, feature level, score level

I. INTRODUCTION

In the literature of pattern recognition and computer vision, there are many fusion-related research works on different levels. Fusion information is a relatively understudied problem because of practical difficulties. It may cause significant classifier performance losses if the best fusion scheme is not relevantly chosen [1].

Several fusion strategies can be roughly classified into three main categories: fusion at an early stage, fusion at a later stage and hybrid fusion. However, many systems that integrate information at an early stage are believed to be more effective than those perform integration at a later stage [2]. Therefore, while it is relatively more difficult to achieve in practice, fusion at early stage has drawn more attention in recent years. There are two types of early fusion: fusion at image level (3D image [3] or 3D/2D image [4]), and fusion at feature level [2]. In fusion at later stage, all classifiers are included in the fusion scheme. Since these individual experts may be correlated, it may not be the best scheme to follow. In this case, there are three fusion sub-levels: score match level [5], rank level [6] and decision level [7]. Kittler et al. [11] presented and developed a common theoretical framework for these combining classifiers. At the first level, similarity scores are combined by various techniques [8], for example, Sum Rule, Product Rule, etc. At the second level, sorted lists computed by classifiers are merged based on different approaches such as Borda Count and Logistic Regression [9]. At the third level, all the candidates of the classifiers are fused by adopting several methods [10], i.e., Majority Vote or Majority Vote with maximum confidence. The last category contains intermediate fusion schemes, such as serial fusion and multilevel fusion. The main motivation of the serial or hierarchical architecture [10] is to filter out the most similar K classes using a simple classifier and then to feed these K classes into a more complex and powerful second classifier. On the other side, there are few works that describe multilevel fusion. In [12], fusion is introduced in both feature level and confidence level for face recognition.

In this work, we propose a general multilevel fusion method that is able to obtain a global sub-optimal solution while lessening the complexity of calculation. The main contributions of this paper are as follows. We propose to use a genetic algorithm with a novel coding strategy for effective feature selection; at the same time an optimal fusion strategy scheme is generated at both feature and matching score level. The remainder of this paper is organized as follows: Adaptive feature and score level fusion strategy is introduced in section II, and section III presents experimental results. Section IV concludes the paper.

II. ADAPTIVE FEATURE AND SCORE LEVEL FUSION STRATEGY

The proposed approach (Fig. 1) is based on genetic algorithm, using a novel coding technique, to search the optimal fusion scheme.

A. Algorithm Overview

The method consists of two steps. In the first step the data is preprocessed and features are extracted. For measurement cost and classification accuracy, Linear Discriminant Analysis (LDA) is used to reduce the dimensionality for each feature type. The second step finds one subset of features that is optimal with respect to the corresponding fusion scheme. So, all features are coded to
form individual “chromosomes” according to the model described in the section II.B.

![Figure 1. The algorithm Overview](image)

Furthermore, these chromosomes are used by a genetic algorithm [13, 14] to encode the trial solution for the current problem. Iterative selection, crossover, and mutation are used to make evolve a new population. At each new generation, a new set of chromosomes is produced, using the fittest genes of the previous generation, for a better solution. Assessment of the satisfactory degree of this solution, encoded as individuals, is reflected in the fitness. Also, the individuals with higher fitness have a high probability of being selected and producing offspring. The crossover operator produces better offspring by exchanging the characteristics of the parents. This enables the most efficient characteristics to be concentrated in the same individual. The mutation operator randomly changes the genetic representation of an individual and tends to inhibit the possibility of converging to a local optimum, rather than the global optimum. The evolution is carried out until a desired solution is arrived, or a pre-specified number of iterations are completed. The final solution with higher fitness represents the optimal fusion strategy.

B. Basic Properties of Genetic Algorithm

We propose a novel coding strategy to select simultaneously the efficient feature and the optimal fusion scheme. This coding strategy divides the chromosome into two parts: Part A and Part B (See Fig. 2). Given \( N \) features, Part A has \( N \) gene positions that correspond to each feature, and represented with integer values: 1 implies that the feature is active and used in feature level fusion; 0 implies that the feature is active and used in score level fusion; -1 implies that the feature is inactive. Part B codes the fusion model that depends on the number \( N_F \) of active features at feature level fusion. In this model, we generate all possible combinations. However, we can’t create a strategy that contains a single feature and we consider that combinations obtained by permutation are equivalent. Part B is also composed of two parts \( P_1 \) and \( P_2 \): \( P_1 \) refers to the model \( M \) and \( P_2 \) associates the features in this model.

![Figure 2. An example of chromosome coding strategy](image)

An example of this representation is illustrated in Fig 2. With Part A as 101101-11, we can generate 4 models \( M_i \), with \( i \) in \( \{1, 4\} \): \( M_1=(6, 0), M_2=(2, 4), M_3=(3, 3), M_4=(2, 2, 2) \). The number of the selected model is represented in the chromosome by its binary code: the model \( M_2 \) is selected and represented by (010) and two vectors \( V_1, V_2 \) are created by concatenation, \( V_1=[F_3, F_4] \) and \( V_2=[F_3, F_1, F_7, F_5] \). The fusion strategy corresponds to a score matching level with \( V_1, V_2, F_1 \) and \( F_6 \). The fitness of this strategy is calculated based on performance rate with simple sum rule in score level fusion. Stochastic universal sampling [15] is used to select best chromosomes “strategies”. Uniform crossover is used only on Part A and random mutation may occur in Part A or Part B on chromosome. Stopping criteria chosen for problem solving is selected from these conditions: 1) whether the number of iterations is over the pre-specific number of generations, 2) whether the best fitness value is beyond the value of fitness limits.

III. EXPERIMENTAL RESULTS

The proposed algorithm is tested in a face recognition application, where the objective is to find an optimal subset of features and their adequate fusion strategy.

A. Database, Experiment Settings and Feature Extracted

The FRGC [16] database is chosen for our experiments. Each face data consists of one 3D face model and its registered 2D color image. 3D faces are preprocessed with techniques in [17]. At the first step, 116 subjects each of which has 4 face models are selected from FRGC v1.0 to train subspace based approaches such as estimating LDA parameters. Two pre-defined data subsets of the FRGC v2.0 database are created to evaluate our algorithm: training and test databases. The training database is composed with a gallery subset (50 subjects) and 470 face scans are treated as probes. The training database outputs the optimal fusion
strategy. For evaluating this strategy, we use a test database with a different gallery subset (50 subjects) and 472 face scans are treated as probes. In our experiments, we only use 3D features containing normal (Nor Vec), binormal (BiN Vec), tangent vector (Tang Vec) [18] and curvature related features. They proved to have the potential for a higher accuracy to describe the surface based events. Four categories of curvature-based features are extracted. The first two types rely on main directions corresponding to maximum (Max Curv) and minimum (Min Curv) curvatures [19]. The last two are their derivatives, i.e., the mean (Mean Curv) and Gaussian (Gauss Curv) curvatures. We further investigate another type of 3D feature based on the anthropometric (Anthr Mes) approach which advocates extracting a signature from some anthropometric points considered the most relevant. So, Part A of chromosome is organized as follows: {Tang Vec, BiN Vec, Nor Vec, Gauss Curv, Max Curv, Mean Curv, Min Curv, Anthr Mes}.

B. Results and Analysis

LDA is applied to reduce dimensionality of all features. One similarity measure of each feature was computed with Nearest Neighbor (NN) using Euclidean distance. TABLE I displays the performance of each feature. As in the table, the best rank-one recognition rate is provided by tangent vectors with 86.22%.

| TABLE I. RANK-ONE RECOGNITION RATE OF INDIVIDUAL TYPE OF FEATURE ON THE FRGC v2.0 DATABASE |
| Max Curv | 73.98 | Mean Curv | 79.59 |
| Gauss Curv | 62.76 | Anthr Mes | 64.8 |
| Min Curv | 73.98 | Tang Vec | 86.22 |
| BiN Vec | 79.59 | Nor Vec | 79.59 |

With a gain of 5.62 percent, the improvement is achieved by SBFS-based classifier selection [20] (See TABLE II). In fact, the near optimal subset found by SBFS-based classifier selection for simple sum technique is {Tang Vec, BiN Vec, Mean Curv, Anthr Mes}. In our work, the optimal strategy fusion is generated based on training database. This strategy is outputs after 50 generations, each generation containing 50 chromosomes, and coded as follows. Part A: 00-1-111-10, Part B: [P1: 000001, P2:5, 6]. The selected strategy consists firstly to concatenate {Max Curv, Mean Curv} in vector V1, Secondly, we use this optimal subset {V1, Tang Vec, BiN Vec, Anthr Mes} in score level fusion. We produce the best rank-one recognition rate 92.35% with the test database. As we can see in TABLE II, Original Sequential Backward Floating Search [1] represents a feature-selection method which learned in training database and achieved a 90.31% rank-one recognition rate on the test database. The proposed genetic algorithm improves rank-one recognition accuracy as compared with other methods [1, 20] in two steps: selecting the most discriminative features and proposing an optimized fusion strategy.

IV. CONCLUSIONS AND FUTURE WORKS

In this paper we propose a framework of fusion strategies that is able to go far beyond the classical early and late fusion. A genetic algorithm is used to find a sub-optimal fusion scheme. This technique is a powerful global optimization method which is based on natural selection and genetics mechanisms. However, it is important to use the suitable coding strategy. Therefore, a new coding technique is developed showing its effectiveness through experiments on the FRGC v2.0 dataset. In fact, the proposed method AFFSFS tunes itself between feature and matching score levels, and produces significantly better results than Original Sequential Backward Floating Search (SBFS) and SBFS-based classifier selection.

In future works, we intend to extend this fusion scheme in order to generate the best model feature-classifier-fusion (FCF). This can be possible if fitness function is dynamic and can select the best classifier for each fusion method. We plan as well to apply this framework to other applications in pattern recognition.

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