An Evolutionary Feature Selection Algorithm for Classification of Human Activities

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Abstract. This paper proposes an evolutionary feature selection algorithm to classify human activities. Feature selection is one of the key issues in machine learning, along with classification when some parts of features are not available or have redundant information. It enhances learning accuracy by selecting essential features and eliminating non-essential features. In the proposed algorithm, a feature selection algorithm integrated with an evolutionary algorithm (EA) is developed. We use the wrapper approach, which repeatedly calls the learning algorithm to evaluate the effectiveness of the selected features. Quantum-inspired evolutionary algorithm (QEA) is utilized as an evolutionary algorithm and multi-layer perceptron (MLP) is used as a classifier. The proposed algorithm is applied to classification of the human activities using smart-phone sensors.

1 Introduction

Real life data have noise which makes subsequent machine learning processes difficult. The task of the classifier could be simplified by eliminating features that are seemed to be redundant for classification. The maintenance of only necessary features could reduce size of the dataset and subsequently allow more comprehensible analysis of the data.

In the feature selection problem, there are two big approaches. The first approach is reducing the dimensionality of the feature set, referred to *feature extraction* [1–4]. It is thought to create new features based on transformations or combinations of the original feature set. Popular dimension reduction algorithms include linear discriminant analysis (LDA), principal component analysis (PCA), locality preserving projection (LPP), neighborhood preserving embedding (NPE), graph optimization for dimensionality reduction with sparsity constraints (GODRSC).

The second approach is selecting essential features. To deal with this approach, *wrapper* and *filter* methods are commonly integrated to select essential features. Filter method selects a subset of features as a preprocessing step, and then learning algorithm is executed. Wrapper method uses a learning algorithm in the feature selection step to evaluate the performance of the feature subset [5, 6]. Such two methods are combined with various mathematical algorithm including mutual information [7], fuzzy-rough set [8], and local-learning [9].

In this paper, wrapper feature selection based on evolutionary algorithm is introduced. Evolutionary algorithm (EA) generates a subset of the features considering both classification accuracy and size of the selected features subset. To demonstrate the effectiveness of the proposed algorithm, the classification of human activities using smartphone sensors is carried out.

The rest of this paper is organized as follow. In Section 2, the quantum-inspired evolutionary algorithm (QEA) is introduced. Section 3 the details of the evolutionary feature selection algorithm is presented. The experimental results are discussed in Section 4 and concluding remarks follow in Section 5.

2 Quantum-inspired Evolutionary Algorithm (QEA)

Building block of classical digital computer is represented by two binary states, '0' or '1', which is a finite set of discrete and stable state. In contrast, QEA utilizes a novel representation, called a Q-bit representation [10], for the probabilistic representation that is based on the concept of qubits in quantum computing [11]. Quantum system enables the superposition of such state as follows:

$$\alpha|0\rangle + \beta|1\rangle \tag{1}$$

where α and β are the complex numbers satisfying $|\alpha|^2 + |\beta|^2 = 1$.

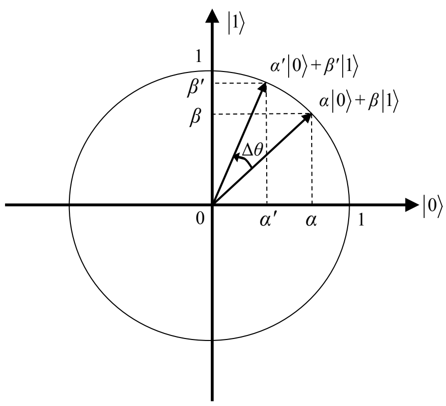

Fig. 1. Qubit described in two dimensional space.

Qubit is shown in Fig. 1, which can be illustrated as a unit vector on the two dimensional space as follows:

$$q_{ji}^t = \begin{bmatrix} \alpha_{ji}^t \\ \beta_{ji}^t \end{bmatrix} \tag{2}$$

$$\mathbf{q}_j^t = \left[\begin{array}{c|c|c|c} \alpha_{j1}^t & \alpha_{j2}^t & \cdots & \alpha_{jm}^t \\ \beta_{j1}^t & \beta_{j2}^t & \cdots & \beta_{jm}^t \end{array} \right] \tag{3}$$

where m is the string length of Q-bit individual, and $j = 1, 2, ..., n$ for the population size n. The population of Q-bit individuals at generation t is represented as $Q(t) = \{\mathbf{q}_1^t, \mathbf{q}_2^t, ..., \mathbf{q}_n^t\}$.

Since Q-bit individual represents the linear superposition of all possible states probabilistically, diverse individuals are generated during the evolutionary process. The procedure of QEA and the overall structure for single-objective optimization problems are described in [10].

3 Evolutionary Feature Selection Algorithm

3.1 Feature Generation

The characteristics of sensor signals can be obtained by extracting features. We extract five features including mean, var, rms, MAD, and IQR from the signals of the triaxial accelerometer and gyroscope. Each feature indicates average, variance, root mean square, mean absolute deviation, and interquartile range, respectively. The values of the features are defined as:

$$\begin{aligned} \text{Mean} &= \frac{1}{L}\sum_{i=1}^{L} x_i & \text{Var} &= \frac{1}{L-1}\sum_{i=1}^{L} (x_i - m) \\ \text{rms} &= \frac{1}{L}\sum_{i=1}^{L} x_i^2 & \text{MAD} &= \frac{1}{L}\sum_{i=1}^{L} |x_i - m| \end{aligned} \tag{4}$$

where L is the length of the signals, and m is mean value. IQR represents the dispersion of the data and eliminates the influence of outliers in the data. The features are extracted from each axis of the triaxial accelerometer and gyroscope, thus an initial set of the features has 30 elements.

3.2 Feature Selection based on Evolutionary Algorithm

Feature selection aims at finding a subset of the features that has the most discriminative information from the original feature set because most of data set from the real life has redundancy. Due to such redundancy, the dimensionality of the data set increases and the subsequent learning processes could have poor performance. In addition, it makes the learning process slow down. Among the feature selection algorithms, we use a randomized approach that could avoid the possibility of local optima problem compared to the other feature selection methods based on mathematical formula. In this paper, a evolutionary algorithm (EA) is used as an operator for the feature selection.

In the classification problem using a feature selection algorithm, there are two approaches mainly used; the *wrapper* approach depicted in Fig. 2 and the *filter* approach depicted in Fig. 3. The wrapper approach uses an actual classification algorithm to find a subset of features, while the filter approach extracts undesirable features out of the feature set before the classification process. Filter method is computationally efficient, but has poor performance compared to wrapper method. Hence, wrapper method is utilized to integrate evolutionary algorithm with learning algorithm.

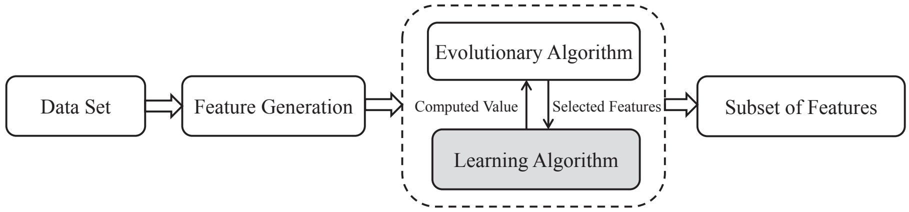

Fig. 2. Wrapper method for the feature selection.

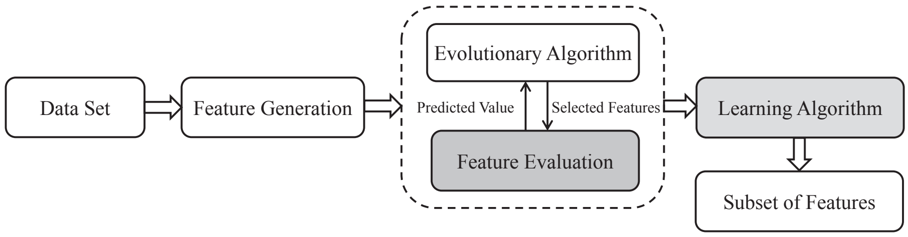

Fig. 3. Filter method for the feature selection.

In this paper, quantum-inspired evolutionary algorithm (QEA) is adopted as an evolutionary algorithm. QEA uses probabilistic binary string which is called Q-bit individual defined as eq. 3. Each feature is linked to each corresponding Q-bit represented in eq. 2. Then, population $\mathbf{B}_j^t$ is generated by observing Q-bit individual, which is binary string. If an element of the population $\mathbf{B}_j^t$ has a value of '1', corresponding feature is selected, otherwise is not selected. A feature subset consisting of the selected features is forwarded to learning algorithm. Overall structure is depicted in Fig. 4.

3.3 Fitness Function

The fitness function evaluates a subset of features designated by the feature selection algorithm, providing classification accuracy and computational complexity. For considering both aspects, the fitness function that contains classification accuracy with size of feature subset is proposed. The proposed fitness function is as follows:

$$\text{fitness function} = \alpha f_1 + \beta \frac{1}{f_2} \tag{5}$$

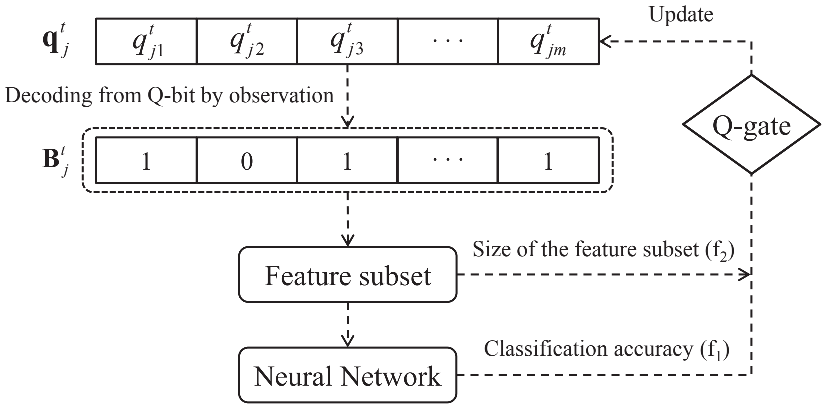

Fig. 4. Feature selection with QEA.

where α, β are parameters that indicate weights of two objectives. The first term f_1 corresponds to the classification accuracy, and second term f_2 corresponds to the number of the selected features. In our experiments, the value of α, β set to 0.6, 0.4.

4 Experimental Result

4.1 Experimental Setup

The proposed algorithm was applied to human activity classification problem using acceleration and gyroscope data in a smartphone. We classified four activities: *sitting in the chair, walking straightly, running straightly, jumping.* The acceleration and gyroscope signals in a smartphone were transmitted to the computer through Bluetooth, and the dataset was obtained from a subject who did activities with a smartphone. Each activity was repeated 10 times. Overall data flow of the hardware platform is depicted in Fig. 5.

4.2 Results

The proposed algorithm was able to find the optimized subset of the features. In the evolutionary feature selection algorithm, the maximum generation was set to 1000. The classification accuracy was highest when 19 features were used. Four human activities were classified with 95% accuracy when the optimized subset of the features was used. The results show that a large number of features did not always guarantee the highest classification accuracy. In the classification problem, the retention of all features is not suitable for classifying data because some features might not have discriminative information to distinguish different data.

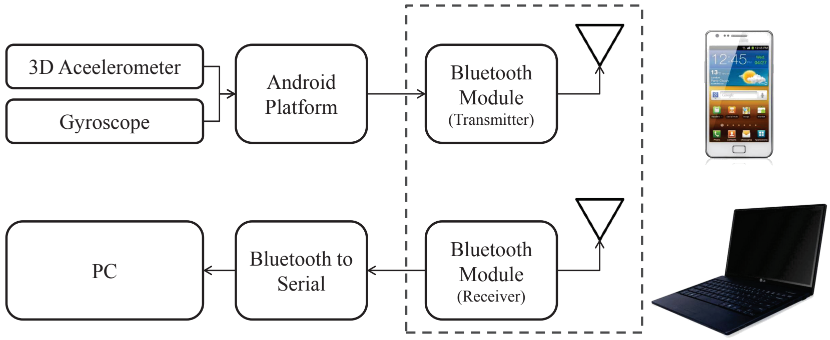

Fig. 5. Overall structure of the hardware platform.

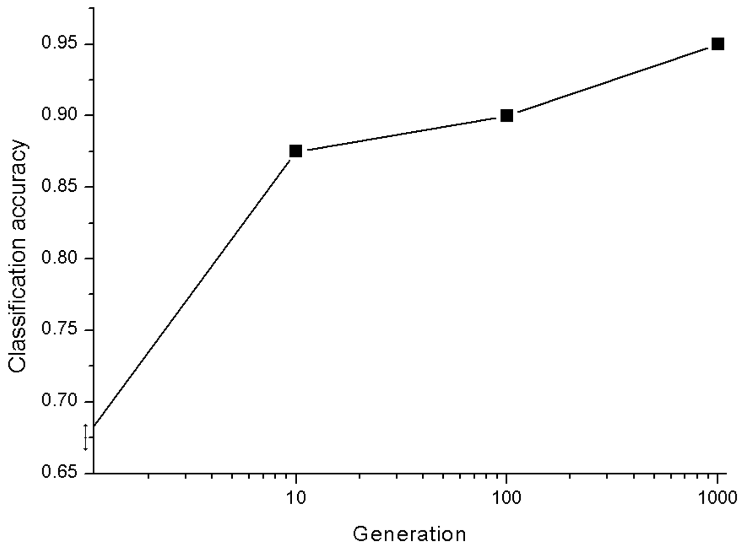

Fig. 6. The classification accuracy according to generation.

5 Conclusions

This paper proposed an evolutionary feature selection algorithm for classification of human activities. As an evolutionary algorithm, quantum-inspired evolutionary algorithm (QEA) was applied to feature selection, and multi-layer perceptron (MLP) was used as a classifier. The proposed algorithm was designed to enhance the classification accuracy and to reduce the size of the feature set. To validate the effectiveness of the proposed algorithm, we carried out the classification of human activities. As a result, we could obtain the subset of the features considering not only learning accuracy but also the size of the feature set, and classify the four human activities with high accuracy.

Acknowledgement This research was supported by the MEST (The Ministry of Education, Science and Technology), Korea, under the Mid-career Researcher Program, supervised by the NRF (National Research Foundation)(2009-0080432, Robust Unified Navigation Technology of Humanoid Robot Using Gaze Control, Posture Learning and Footstep Planning).

This research was also supported by the MOTIE (The Ministry of Trade, Industry and Energy), Korea, under the Human Resources Development Program for Convergence Robot Specialists support program supervised by the NIPA (National IT Industry Promotion Agency)(H1502-13-1001, Research Center for Robot Intelligence Technology).

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