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Hybrid of artificial immune system and particle swarm optimization-based support vector machine for Radio Frequency Identification-based positioning system ☆

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ABSTRACT

This study intends to propose a hybrid of artificial immune system (AIS) and particle swarm optimization (PSO)-based support vector machine (SVM) (HIP–SVM) for optimizing SVM parameters, and applied it to radio frequency identification (RFID)-based positioning system. In order to evaluate HIP–SVM's capability, six benchmark data sets, Australian, Heart disease, Iris, Ionosphere, Sonar and Vowel, were employed. The computational results showed that HIP–SVM has better performance than AIS-based SVM and PSO-based SVM. HIP–SVM was also applied to classify RSSI for indoor positioning. The experiment results indicated that HIP–SVM can achieve highest accuracy compared to those of AIS–SVM and PSO–SVM. It demonstrated that RFID can be used for storing information and in indoor positioning without additional cost.

1. Introduction

Radio frequency identification (RFID) has the characteristics of contactless, to be reused, durable, the mass storage capacity and multi-read and is suitable to be used in cargo tracking and information collection. More and more applications have been developed for logistics, like warehouse management and in-transit inventory management (Weinstein, 2005). In addition to the applications mentioned above, RFID may also be applied in the indoor positioning system. RFID is one of the recent wireless communication technologies. Due to some physic characteristics, like received signal strength index (RSSI) and the arrival time of radio frequency (RF) between the interrogator and tag, it can be utilized to locate the goods position or picking cart position. After knowing the cart position, once a new order is coming, it can be used to plan the picking rout in order to minimize the picking distance.

On the other hand, support vector machine (SVM) (Vapnik, 1995) has been widely applied in many areas for classification. Thus, this study intends to present a novel SVM based on a hybrid of artificial immune system (AIS) and particle swarm optimization (PSO) (HIP–SVM). The hybrid of AIS and PSO is employed to optimize the parameters combination for SVM. In order to assess HIP–SVM's capability, six benchmark data sets, Australian, Heart disease, Iris, Ionosphere, Sonar and Vowel, are first employed. Then, HIP–SVM is applied to classify RSSI for indoor positioning.

The rest of paper is organized as follows. Section 2 presents some related literature survey, while the RFID-based position system is proposed in Section 3. Section 4 demonstrates the capability of the proposed HIP–SVM using six benchmark data sets. Section 5 shows the model evaluation results the proposed RFID-based position system through simulation. Finally, concluding remarks are made in Section 6.

2. Background

This section will briefly introduce radio frequency identification, support vector machine, particle swarm optimization, and artificial immune system.

2.1. Radio frequency identification (RFID)

RFID is a kind of technology, which employs radio wave to identify an object, and typical RFID system consists of four parts: reader, tag, antenna, and host computer system (Ranky, 2006; Shepard, 2005). The current positioning system could be divided into indoor and outdoor ones. The generally known outdoor systems include Global Positioning System (GPS) and car navigation systems combined with electronic map. The common indoor

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positioning systems comprise infrared (Want, Hopper, Falcão, & Gibbons, 1992), ultrasonic (Priyantha, Chakraborty, & HariBalakrishnan, 2000), and wireless local area network (WLAN) positioning (Bahl & Padmanabhan, 2000). RFID has been studied in recent years due to its newfound attention. As compared to outdoor positioning, indoor positioning system may be easily affected by ambient environment during measurement of signals. This may cause instability and greater variation of signals. Moreover, indoor space is narrow, accurate positioning is more difficult and also is more important.

Positioning system provides actual position information of an object in a specific space according to the space feature. For RFID system, specific space is signal range of wireless access points arranged by organizations, also called RFID signal space. The features of the space are collectively referred to as features of RFID wireless signals, which can be RSSI or features of wireless signals calculated according to strength, such as signal difference of two wireless points or strength decrease difference of RFID due to obstruction of object. The recently employed positioning techniques include Triangulation, Scene Analysis and Proximity (Hightower & Borriello, 2001; Ni, Liu, Lau, & Patil, 2003).

2.2. Support vector machine

Support vector machine (SVM), proposed by Vapnik (1995), is a machine learning method based on the statistical theory. SVM applies Separating Hyperplane to separate two or several types of data. Due to its promising performance, SVM has been widely applied in many areas, like face detection (Osuna, Freund, & Girosi, 1997) and object detection (Pontil & Verri, 1998). In practice, there are many different types of data. The SVM can be divided into Linear Separable, Linear Non-separable (Cortes & Vapnik, 1995) and Non-linear Separable (Boser, Guyon, & Vapnik, 1992).

The original SVM handles binary classification issue, and can also be extended to multi-class classification. It usually combines with several binary classifiers, and the common three methods include One-against-all (Bottou et al., 1994), One-against-one (Kreβel, 1999) and Directed Acyclic Graphic SVM (DAGSVM) (Platt, Cristianini, & Shawe-Taylor, 2000).

The SVM parameters are often determined by the users, but these parameters have important influence on the classification result (Keerthi & Lin, 2003). Grid Algorithm is the common method to optimize penalty constant C and kernel function parameters (Hsu et al., 2010). However its computational efficiency is not good. Huang and Wang (2006) proposed genetic algorithm-based SVM for optimizing parameters and feature selection, and it was further applied in credit rating (Huang, Chen, & Wang, 2007). Lin, Ying, Chen, and Lee (2008) used particle swarm for optimizing SVM parameters (PSO–SVM), and compared them with GA-SVM (Huang & Wang, 2006). The findings show PSO–SVM has good performance in 6 of the 10 data sets.

2.3. Particle swarm optimization

Particle swarm optimization (PSO) was first designed by Kennedy and Eberhart in 1995. It shares many similarities with evolutionary computation techniques such as genetic algorithms (GAs). Systems are initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolutionary operators, such as crossover and mutation. In the PSO, the potential solutions, called particles, move through the problem space by following the current optimum particles.

In the original PSO, particles are represented as $X_i = (x_{i1}, x_{i2}, \ldots, X_{iD})$, which represents a potential solution to a problem in D-dimensional space. Each particle keeps a memory of its previous best position Pbest, and a velocity along each dimension, represented as $V_i = (\upsilon_{i1}, \upsilon_{i2}, \ldots, \upsilon_{iD})$. At each iteration, the position of the particle with the best fitness value in the search space, designated as g, and the P vector of the current particle are combined to adjust the velocity along each dimension, and that velocity is then used to compute a new position for the particle (Eberhart & Kennedy, 1995). This method can be divided into the GBEST and LBEST versions, whose main difference is their definition of what is the best. In the GBEST version, the particle swarm optimizer keeps track of the overall best value, and its location, obtained thus far by any particle in the population, which is called *gbest* (P_{gd}). For the LBEST version, in addition to *gbest*, each particle keeps track of the best solution, called *lbest* (P_{gd}), attained within a local topological neighborhood of particles. However, the particle velocities in each dimension are held to a maximum velocity, V_{max}, and the velocity in that dimension is limited to V_{max}. The updating rule is as follows:

$$V_{id}^{new} = V_{id}^{old} + c_1 \cdot rand_1 \cdot (P_{id} - X_{id}) + c_2 \cdot rand_2 \cdot (P_{gd} - X_{id}) \tag{1}$$

$$X_{id}^{new} = X_{id}^{old} + V_{id}^{new} \tag{2}$$

where c_1 and c_2 determine the relative influence of the social and cognitive components (learning factors), while $rand_1$ and $rand_2$ denote two random numbers uniformly distributed in the interval $[0,1]$.

In the original version, the maximum velocity V_{max} serves as a constraint to control the global exploration ability of a particle swarm. As stated above, a larger V_{max} facilitates global exploration, while a smaller V_{max} encourages local exploitation. The concept of an inertia weight was developed to better balance exploration and exploitation in order to eliminate the needs of V_{max}. The inclusion of an *inertia weight* in the particle swarm optimization algorithm was first reported by Shi and Eberhart (1998a, 1998b). The updating rule is as follows:

$$V_{id}^{new} = W \cdot V_{id}^{old} + c_1 \cdot rand_1 \cdot (P_{id} - X_{id}) + c_2 \cdot rand_2 \cdot (P_{gd} - X_{id}) \tag{3}$$

$$X_{id}^{new} = X_{id}^{old} + V_{id}^{new} \tag{4}$$

where W is an inertia weight. Eberhart and Shi (2001a) suggested that inertial weight can be decreased linearly from 0.9 to 0.4. They (Eberhart & Shi, 2001b) also recommended that it can also be set as 0.5 + rand/2 in order to let inertial weight in the interval of $(0.5, 1)$. van der Merwe and Engelbrecht (2003) suggested to set inertia weight as 0.72.

The work done by Clerc (1999) indicates that the use of a *constriction factor* may be necessary to insure convergence of the PSO. The updating rule is as follows:

$$V_{id}^{new} = K \times [V_{id}^{old} + c_1 \times rand_1 \times (P_{id} - X_{id}^{old}) + c_2 \times rand_2 \times (P_{gd} - X_{id}^{old})] \tag{5}$$

$$X_{id}^{new} = X_{id}^{old} + V_{id}^{new} \tag{6}$$

$$K = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|}\, \varphi = c_1 + c_2 \quad \text{and} \quad \varphi > 4 \tag{7}$$

where K is a constriction factor.

Social interaction is an important factor to improve PSO performance. To enhance the social interactions in the algorithm, Zhao, Guo, Bai, and Cao (2006) put forward a new method of improved PSO. They propose the use of an improved adaptation strategy with enhanced social interactions for PSO. This adaptation strategy uses the information of more particles to control the mutation operation. It also extends the original formulas of PSO to search for the global optimal solution more effectively. This is similar to the human society in that a group of leaders can make better decisions.