A SVM-based AI Design for Interactive Gaming

Abstract – Interactive gaming requires automatic processing on large volume of random data produced by players on spot, such as shooting, football kicking, boxing etc. In this paper, we describe an artificial intelligence approach in processing such random data for interactive gaming by using a one-class support vector machine (OC-SVM). In comparison with existing techniques, our OC-SVM based interactive gaming design has the features of: (i) high speed processing, providing instant response to the players; (ii) winner selection and control by one parameter, which can be pre-designed and adjusted according to the game design needs, i.e., level of difficulties; Experiments on numerical simulation support that the proposed design is robust to random noise, accurate in picking up winning data, and convenient for all interactive gaming design.

Key words: Interactive gaming, AI gaming, and SVM

1. Introduction

Over the past decades, artificial intelligence in computer gaming development has become an increasingly important research area and many researchers attempted and reported many algorithms across a number of disciplines including interactive gaming, character behaviour control, events and activity simulation etc. Theoretical and practical advancements have been made in building human level AI systems, which enables data from other entertainment sources such as 'star trek', 'star wars' etc. to seamlessly integrate with all level human capabilities. As a result, interactive gaming assisted with AI techniques has evolved as one of the most important research topics within the gaming industry as well as the research community [1-2]. In a stream of reports, papers, and research seminars, J. Laird [1] addressed this topic on the basis of reviewing existing research on AI and gaming to describe different game genres and specify the roles that human-level AI could play within these genres. In [3], neural network based approaches are reported to provide intelligence for characters in fighting action games. The proposed approaches include three phases of designs, which include basic game rule learning and matches against randomly acting opponents, evaluation of decision fitness by using the relative score change caused by the decision, and training of neural network by using the score difference and the previous input and output values which induced the decision. The opponents' past actions are also utilized to find out the optimal counter-actions for the patterns, and experiments show that significant understanding of the game rules is achieved by the proposed AI algorithm. AI techniques are also playing leading roles for character-based design and development [4-5], which is essentially organized around the topic of artificial characters. The work reported in [5] introduces an intermediate architecture that fits between games and AI elements, and assess the feasibility of improving quality of game AI.

Essentially, the AI system looks over the shoulder of a player while they are taking part and learns how they deal with issues incurred in fighting games, interactive games, and all other games which require significant speed in responding and reactions.

As one of the most popular machine learning approaches, SVM has received tremendous attention in a number of areas to deal with learning, training and optimising problems. General SVM uses a kernel-mapping technique to separate linearly non-separable cases in high dimensional space [6]. SVM not only separates data from different classes, but also separates data to its maximum margin. In other words, SVM not only divide mixed data sets into classes, but also optimize such a classification. However, the weakness of general SVM lies in the fact that it requires labeled data sets to get it trained, yet interactive game design requires close-to-real randomness and thus responses made by players or computer simulated opponents could be very diversified. To this end, the data produced by such a random responses could be difficult to label, or manual labeling could require significant resources and time consuming. To this end, we introduce a one-class-SVM and design an AI mechanism, which can automatically process the random response data sets without any labeling process, yet capable of detecting those characteristics out of the response data randomly generated by either players or computer simulated opponents.

One-class-SVM is essentially an extension of support vector machines [7] used for detecting the outliers [8, 9]. The idea is that it first maps the data into high dimensional space, and then maximizes the margin between the mapped data and the origin. A trade-off parameter ν is introduced to control the maximum percentage of outliers in the dataset. The one-class-SVM overcomes the shortcomings of traditional SVMs in coping with the one class data with noise, and is supposed to possess good generation ability in outlier detections. The rest of the paper is organised into three further sections, where section 2 is to describe the proposed AI design for interactive gaming based on one-class-SVM. Section 3 reports the experimental results, and finally, section 4 make concluding remarks.

2. The Proposed AI Design

The scenario for interactive gaming is that among all the responses generated by players or the simulated computer opponents, only a small proportion represents high level hits, which need to be detected and picked up for design of reactions. This is a basic mechanism to make the game play more challenging, which can attract players to learn and improve their skills. Such a scenario can be described by a data set with $T = \{x_1, x_2, \cdots, x_l\}$, $x \in R^N$, as shown in Figure-1 for a two dimensional case. The task is to find a function f that generates the value “+1” for most of the vectors in the data set (marked by stars in Figure-1-(a)), and “-1” for the other very small part (circles in Figure-1-(a)). The Strategy for such a classification and detection is to use a one-class-SVM and map the input data into a Hilbert space *H* according to a mapping function $X = \phi(x)$, as shown in Figure-1-(b), and separate the data from the origin to its maximum margin.

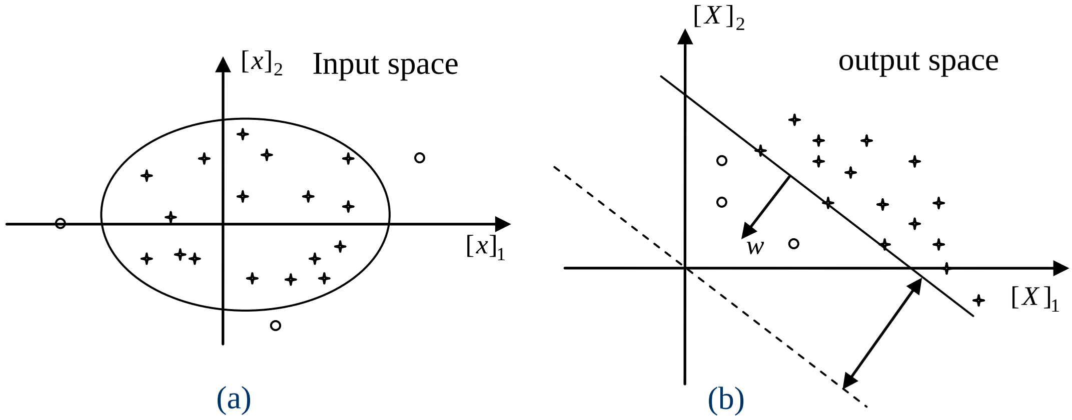


Figure 1 *Data mapping by one-class-SVM from input space (a) to output space (b)*

As a result, to separate the mapped data from the origin to its maximum is equivalent to solving the following quadratic optimisation problem:

$$\min_{w \in F} : \quad \tfrac{1}{2} \| w \|^2 + \frac{1}{\nu l} \sum_i \xi_i - \rho \tag{1}$$

$$\text{s.t.} \quad f(x) = w.\phi(x_i) - \rho \geq -\xi_i, \xi_i > 0, i = 1, \cdots, l \tag{2}$$

Where $\nu \in (0,1)$ is the parameter to trade-off between the ordinary response and high performing response in the data set, that a maximum of $\nu \times 100\%$ are expected to return negative values according to $f(x) = w.\phi(x) - \rho$. ξ_i are slack variables acting as penalties in the objective function. Therefore, based on its dual representations, the one-class-SVM is to solve the following problems:

1. Select a kernel function $K(x, x')$ in Hilbert space H, and the trade-off parameter ν to solve the following optimization problem and find the solution $\alpha^* = (\alpha_1^*, \cdots, \alpha_l^*)$:

$$\min_{\alpha} : \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j K(x_i, x_j) \tag{3}$$

$$\text{s.t.} \quad 0 \le \alpha_i \le 1/(\nu.l), i = 1, \cdots, l \tag{4}$$

Where $K(x_i, x_j) = \phi(x_i).\phi(x_j)$ is the kernel function, and $\sum_{i=1}^{l} \alpha_i = 1$.

2. Select any α^* which satisfies $0 < \alpha^* < 1/(\nu.l)$, and calculate the bias $\rho = \sum_{i}^{l} \alpha_i^* K(x_i, x_j)$. The vectors that satisfies $0 < \alpha^* < 1/(\nu.l)$ are called support vectors.

3. Integrate the decision function $f(x) = \sum_{i=1}^{N_{sv}} \alpha_i^* K(x_i, x) - \rho$, and if $f(x) \ge 0$, return +1. Otherwise, return the real negative value. N_{sv} is the number of support vectors.

It is proved [7] that $\nu \times 100$ is the upper bound percentage of data that are expected to be outliers in the training data, and a vector x_i is detected to be outlier in the training set, if and only if $\alpha_i = 1/(\nu l)$. α_i is the parameter directly determines the sensitivity of outlier detection using one-class-SVM.

Figure-2 illustrates the structure of our proposed AI interactive game design, where the one-class-SVM is taken as the core of the response data processing. Depending on the response data capture mechanisms, further data pre-processing can be designed to improve the SVM based response data selection and classification. In our simulated experiments, we designed the input response vector to contain the location of the response, and the strength of the response. As a result, the input data is a vector of three elements. Following the SVM-based data detection, a basic clustering [9] is designed as a post-processing to cluster the detected response data into three categories, outstanding, excellent, and good, to enable the game designers to allocate appropriate awards to the players' performances.

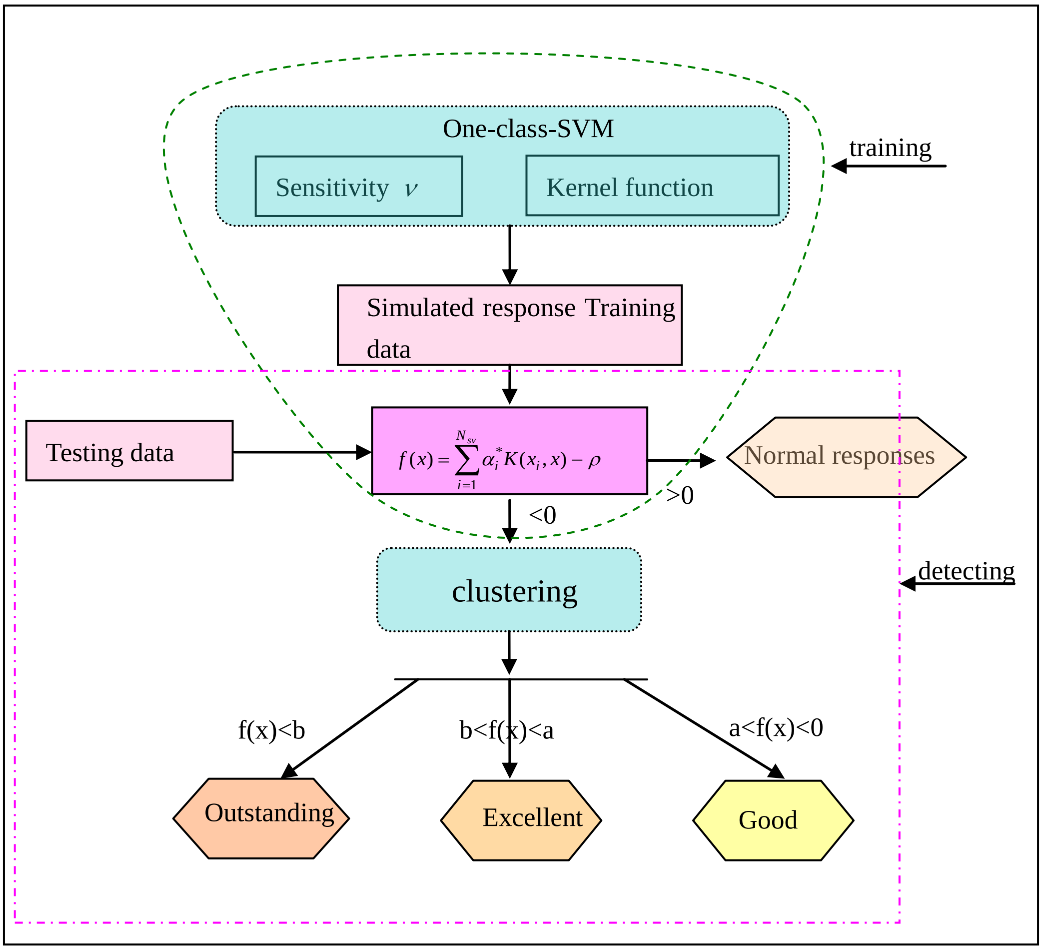
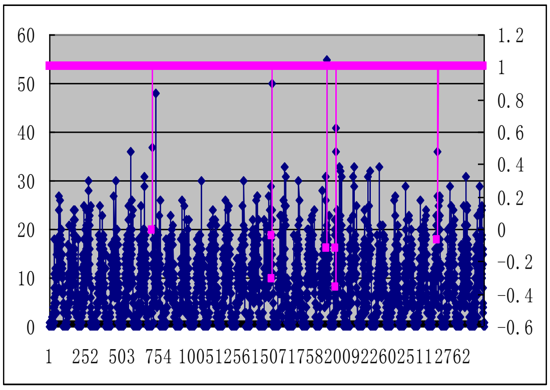


Figure 2 *Structural illustration of the SVM-based AI interaction design*

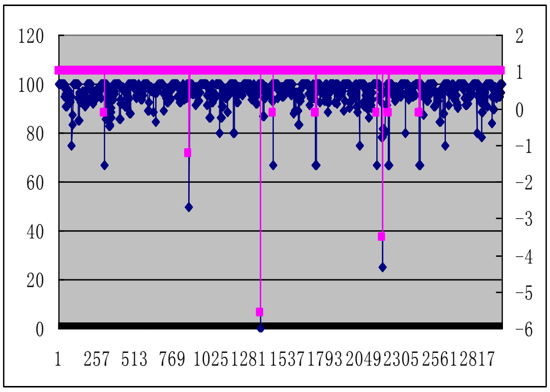
3. Simulated Experiments and Evaluation of the Proposed AI Design

In this Section, numerical experiments are carried out to demonstrate the effectiveness of the SVM-based response data processing. To evaluate the proposed AI interactive algorithm, we designed a simple interactive game to collect the training and testing data, where response is simulated by a pseudo-random generation on a computer screen. While its hit-on-screen location is represented by two coordinates (x, y), its hitting strength can be represented by the intensity value of its display on a grey level scales [0, 255]. To simulate the different contexts and the varying nature of the input data content, we randomly added bias data into the input data capture and asked different players to generate the random input vectors. Following that, performance evaluation and interaction is simulated by the proposed SVM-based system as illustrated in Figure 2.

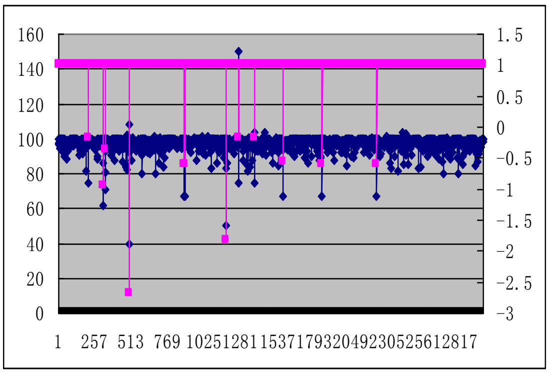
Figure 3 illustrates the simulated experimental results, where the pink colour highlighted are the high performing responses that need to be further classified to determine their awards, and those blue colour highlighted are ordinary responses that do not receive any awards. As seen, not only those high performing responses are effectively detected by the SVM-based AI system, but also their context be adapted to automatically by the proposed system.



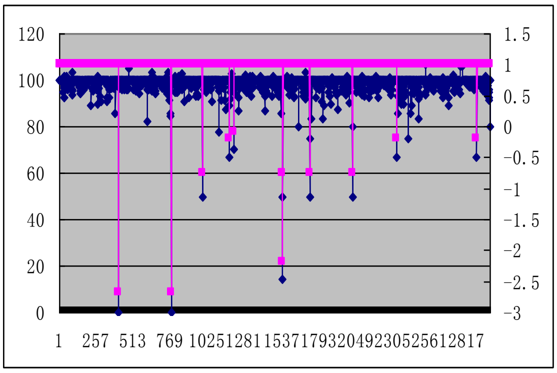
(a) player-1



(b) player-2



(c) player-3



(d) player-4

4. Summary and Conclusion

While existing AI techniques developed for interactive gaming are mostly focused on neural networks and rule-based approaches, we propose a SVM-based approach in this paper to illustrate the effectiveness and efficiency in processing responses and generate reactions. Compared with other AI techniques, the proposed has the features of: (i) self-adaptive to the response data content by controlling one trade-off parameter; (ii) detection of high-performing responses according to the context the responses are generated; (iii) training does not require any labelled data, which can be very useful for circumstances where manual labelling is labour intensive and time consuming. Following the proposed AI design, a number of options can be further designed for specific reactions to the detected responses, such as awards, penalties, or any other actions that can further stimulate responses etc. Therefore, the proposed AI design can have many useful applications in practical computer game design when interaction is required.

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