Haar Wavelets for Online-Game Player Classification with Time Warping

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Abstract

Online-game players' action sequences are an important source of knowledge for understanding players' behaviors. However, they usually contain noisy and/or redundant parts making their lengths unnecessarily long. In this paper, we apply the Haar wavelet transform to action sequences and reconstruct them from selected wavelet coefficients. By this, more compact sequences representing players' salient features are obtained. Experimental results indicate that this approach is effective in terms of the classification performance when the k-nearest neighbor classifier is used for classifying players based on the dynamic time warping distances between reconstructed sequences.

1 Introduction

To keep online-game players in the game, it is necessary that players' demands are grasped and fulfilled, and that appropriate contents tailored for each player or each specific group of players are made. In virtual worlds such as online games, players are typically identified by their characteristics as "Killers", "Achievers", "Explorers", and "Socialisers" [1]. For each player type, provision of game contents according to players' favorites should be performed. Examples of such contents include those with more hunting opportunities, a wider variety of collectable items, longer-journey missions, and higher frequency of social events for Killers, Achievers, Explorers, and Socialisers, respectively.

Online-game players' action sequences are a crucial source of knowledge for classifying player types. However, they usually contain noisy and/or redundant parts making their lengths unnecessarily long. Rather than using action sequences directly in player classification, our previous works used the normalized action frequency vector (NAFV) [2] and the Hidden Markov Model (HMM) [3]. NAFV requires no parameter settings, has low computational costs, and effectively classifies players when their action frequencies are distinctly different, but is less effective when such differences are less apparent even though action orders are dissimilar. HMM [4] is a powerful tool for classifying sequence data, but its performance depends on the structure and initial parameters.

In a more recent paper [5], we proposed a parameter-less approach using action transition probability considering action information in both frequency and order. However, because action transition probability represents only local changes in a sequence of interest, this approach is not suited for classifying players whose local behaviors are similar, but with different global structures, such as, classification of Type-I players performing mission A before mission B and Type-II players performing the two missions in the opposite order.

In this paper, we apply the Haar wavelet transform [7] to action sequences and reconstruct them from selected wavelet coefficients. By this, more compact sequences representing players' salient features, covering both local and global information, are obtained. We employ the k-nearest neighbor classifier [8] for classifying the type of an unknown player, where dynamic time warping [6] is used for computing the distances between the reconstructed sequence of the unknown player and those of known players. The approach is evaluated with action sequences from an experimental online game called "The Ice" under development at the authors' laboratory.

The rest of the paper is organized as follows. In the next section, we describe the Haar wavelet transform. Then, we describe dynamic time warping. Next we propose a method for selecting wavelet coefficients, which is followed by performance evaluation, our conclusions, and future work.

2 Haar Wavelet Transform

Here, we describe Haar wavelet decomposition and reconstruction. Decomposition is a process to obtain Haar wavelet coefficients from an action sequence. Reconstruction is a process to recover the original sequence from the obtained coefficients; a method for selecting coefficients to achieve more compact sequences representing salient features will be given in Section 4.

2.1 Decomposition

First we assume that the length, L, of a sequence of interest is a power of 2 and $q = \log_2(L)$.

The ith Haar wavelet coefficient at resolution order k, $d_{(k,i)}$, can be derived by

$$d_{(k,i)} = \frac{x_{(k+1,2i-1)} - x_{(k+1,2i)}}{2}, \tag{1}$$

where $x_{(k,i)} = \frac{x_{(k+1,2i-1)}+x_{(k+1,2i)}}{2}$ is the ith average at order k between the two corresponding adjacent values at order $k+1$. Note that with this representation, $k_{max} = q$, and the original sequence is represented by $x = x_{(q,1)}, x_{(q,2)}, \ldots, x_{(q,L)}$.

An example of Haar wavelet decomposition of the sequence 8, 6, 2, 3, 4, 6, 6, 5 is shown below.

Resolution	Averages $x_{(k,i)}$	Coefficients $d_{(k,i)}$
k=4	8,6,2,3,4,6,6,5	-
k=3	7, 2.5, 5, 5.5	1, -0.5, -1, 0.5
k=2	4.75, 5.25	2.25, -0.25
k=1	5	-0.25

2.2 Reconstruction

Reconstruction of a given sequence from its Haar wavelet coefficients and averages is performed by the following formulas.

$$x_{(k,2i-1)} = x_{(k-1,i)} + d_{(k-1,i)} \tag{2}$$
$$x_{(k,2i)} = x_{(k-1,i)} - d_{(k-1,i)} \tag{3}$$

3 Dynamic Time Warping for Action Sequences

3.1 Action Coding

Let O denote the set of action symbols of interest and $|O|$ the number of them. As done in [6], an action sequence $S = S(1), S(2), \ldots, S(L)$ is numerically coded into an $|O| \times L$ time-series matrix $X = [X(1), X(2), \ldots, X(L)]$, where $X(i)$ is a column vector with the element indexing the action symbol of $S(i)$ being 1 and the other elements 0.

For example, consider the set of action symbols $O = \{A, B, C\}$, thus $|O| = 3$. In this case, the symbols A, B, and C are represented by column vectors $[100]^t$, $[010]^t$, and $[001]^t$, respectively. In case of an action sequence, say, $S = A, B, C, C$, it will be coded to $X = [[100]^t, [010]^t, [001]^t, [001]^t]$.

3.2 Dynamic Time Warping

Two time series of interest are considered similar if they have the same structures, i.e., rise and fall patterns, although they might have different scales in the time axis. A good measurement for deriving the distances between such series is the dynamic time warping (DTW) distance. The DTW distance between time-series matrices X and Y, $D(X,Y)$, having the length of L_X and L_Y, respectively, is defined as follows[6]:

$$D(X,Y) = g(L_X, L_Y), \tag{4}$$

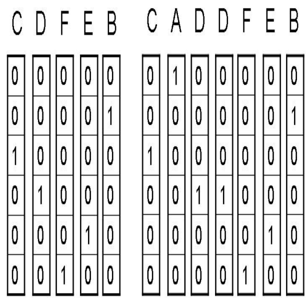

Figure 1: Time-series matrices X and Y

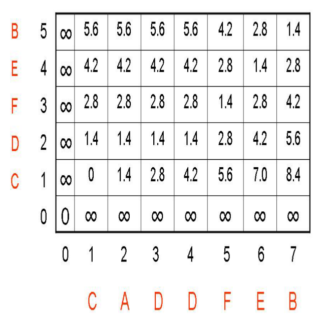

Figure 2: Derivation of the dynamic time warping distance between X and Y

where

$$g(i,j) = min \begin{cases} g(i,j-1) + d(i,j) \\ g(i-1,j-1) + d(i,j) \\ g(i-1,j) + d(i,j) \end{cases} \tag{5}$$

$$g(i,0) = \begin{cases} 0 & i = 0 \\ \infty & i > 0 \end{cases} \tag{6}$$

$$g(0,j) = \begin{cases} 0 & j = 0 \\ \infty & j > 0 \end{cases} \tag{7}$$

and $d(i,j)$ is the Euclid distance between $X(i)$ and $Y(j)$.

For example, let us consider a set of symbols $S = \{A, B, C, D, E, F\}$ and two action sequences $x = C, D, F, E, B$ and $y = C, A, D, D, F, E, B$. The DTW distance between the corresponding time-series matrices X and Y, shown in Fig. 1, $D(X, Y)$, is 1.4, the derivation of which is shown in Fig. 2.

4 Distance Measure between Action Sequences

Given a set of action symbols O, below we describe our procedure for computing the distance between two action sequences of interest.

- Derive the corresponding time-series matrix X for an action sequence of interest x having the length of L[1].

- Decompose each row in X to obtain Haar wavelet coefficients.

- Reconstruct each row in X with selected Haar wavelet coefficients as follows:

  Following the same recipe in [7], the number of Haar wavelet coefficients in use is heuristically set to $\min(L-1, \log_2 L \times 4)$, and reconstruction of each row in X is started from the coefficient at the lowest resolution order, i.e., $d(1,1)$, to those at the adjacent higher order, and so on. In [7], for the case where $\log_2 L \times 4 \geq L - 1$, if the number of remaining coefficients that must be selected for reconstruction is less the number of coefficients at the current resolution order, then all coefficients at that resolution order are reset to zero and then used for reconstruction. However, in this paper, we propose to select the remaining coefficients according to their total energy value in decreasing order, where the total energy value of $d_{(k,i)}$, $E_{(k,i)}$, is defined as

  $$E_{(k,i)} = \sum_{n=1}^{|O|} d^2_{(n,k,i)}, \tag{8}$$

  where $d_{(n,k,i)}$ is $d_{(k,i)}$ decomposed from row n of X. The other unselected coefficients at the same resolution order are reset to zero and then used for reconstruction. Finally, similar to [7], for each reconstructed row of X, repetitive and consecutive elements will be sampled down to one element.

[1]Henceforth, we assume that the length L of each action sequence is adjusted such that L is a power of 2.

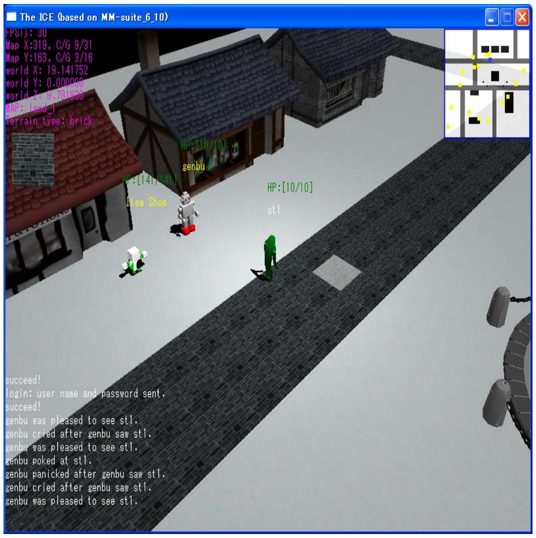

Figure 3: A screen shot of The ICE

- Use the sum of the DTW distances between each row of the reconstructed time-series matrices X and Y as the distance measure between action sequences x and y.

5 Players' Logs

In our study, we obtained players' logs from an experimental online game called The ICE, under development at the authors' laboratory, a screen shot of which is shown in Fig. 3. The main game objects involved in the study were the mission master (MM) whose role was to assign a mission to a player character (PC); three non-player characters (NPCs), Ceris, Rodth, and Gelec, statically located at different locations whom PC must interact with (chat, help, trade) in order to complete the mission; the item-shop NPC from which PC bought items; and monster ants, randomly located throughout the map, that PC must exterminate.

A group of 30 male subjects, on average 20 years of age, participated. These subjects consisted of third-year and fourth-year undergraduate students in computer science with no experience in playing The ICE. They were equally divided into three subgroups G1, G2, and G3. The members of each subgroup were then asked to complete three mission sessions in the following order:

G1:M1 session→M2 session →M3 session,

G2:M3 session →M1 session →M2 session,

G3:M2 session →M3 session →M1 session.

During a mission session, the subjects were asked to repeatedly perform their mission. They were allowed, however, to quit on their own will. In addition, they could freely move and attempt any command, but were not allowed to perform an unassigned mission. A brief description of each mission is given as follows:

M1(Item Delivery): PC has to deliver an item given by MM to a specific NPC and then deliver an item from that NPC to another NPC, and so on.

M2(Item Trade): PC has to trade with NPCs to increase the amount of money initially given by MM. It uses the initial money to buy one of the three items from the item-shop NPC and sells the item with a higher price to one of the three NPCs who only buys a particular item.

M3(Monster Ant Extermination): PC must help Rodth by exterminating five monster ants (MA).

After examining their logs, we unsurprisingly found that most players soon omitted their game missions and started playing the game on their own will, making it difficult to correctly classify them based on their logs. As a result, for our evaluation below, we selected four players from each sub-group who most sincerely played the assigned missions.

6 Performance Evaluation

As a classifier, we use the k nearest neighbor (k-nn) classifier. We examine the classification performance in three cases, differing from each other in computation of the distance between a pair of two players of interest, i.e.,

Case 1 where the proposed distance measure (the sum of the DTW distances between each row of the reconstructed time-series matrices) was used,

Case 2 where the sum of the DTW distances between each row of the original time-series matrices was used, and

Case 3 where the sum of the Euclid distances between each row of the action-transition-probability matrices [5] was used.

Tables 1, 2, and 3 show the classification performance for each case over three variations of k, where each result was obtained by the leave-one-out cross-validation method [8]. In these tables, the ijth element indicates the number of times the k-nn classifier labels an unknown player of subgroup Gi to subgroup Gj. As can be seen from the tables, the performance of the k-nn classifier in case 1 outperforms those of the other cases.

We analyzed the results and found that the k-nn in case 2 had the difficulty in identifying G3 because partial sequences of an action called "attack" typically seen in M3 were also seen in M2. However, the k-nn in case 1 did not have such difficulty indicating that the proposed distance measure is more reliable. The k-nn in case 3 had the worst performance because the distance measure in [5] can not cope with global structures, i.e., the order of missions; however, it could well classify the players in G1 because they walked a lot during the play, making their transition probability from "walk" to "walk" relative high and hence easily classifiable.

7 Conclusions and Future Work

In this paper, we proposed a distance measure between players' action sequences for use in classification of online-game players. The proposed distance measure is the dynamic time warping distance between the reconstructed time-series matrices of a pair of players of interest, where the Haar wavelet transform is applied to decompose time-series matrices derived from the corresponding action sequences and to reconstruct them based on a particular set of Haar wavelet coefficients selected by the proposed energy-based method. Our performance evaluation with the online game "The ICE" indicates that the k-nn classifier using the proposed distance measure outperforms those using other existing distance measures. Our future work is to apply the proposed distance measure to online-game player clustering and visualization.

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Table 1: Classification performance for case 1

	G1	G2	G3
G1	3	1	0
G2	1	3	0
G3	0	0	4

$k = 1$

	G1	G2	G3
G1	3	0	1
G2	1	3	0
G3	0	0	4

$k = 3$

	G1	G2	G3
G1	2	1	1
G2	1	3	0
G3	1	0	3

$k = 5$

Table 2: Classification performance for case 2

	G1	G2	G3
G1	4	0	0
G2	0	4	0
G3	3	1	0

$k = 1$

	G1	G2	G3
G1	4	0	0
G2	0	4	0
G3	2	2	0

$k = 3$

	G1	G2	G3
G1	4	0	0
G2	1	3	0
G3	3	1	0

$k = 5$

Table 3: Classification performance for case 3

	G1	G2	G3
G1	2	1	1
G2	1	0	3
G3	0	2	2

$k = 1$

	G1	G2	G3
G1	3	0	1
G2	1	0	3
G3	2	2	0

$k = 3$

	G1	G2	G3
G1	3	0	1
G2	2	0	2
G3	1	3	0

$k = 5$

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