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Gender Recognition Based on Gait Using Multi-View Fusion

Zhang De*

School of Electrical and Information Engineering, Beijing University of Civil Engineering and Architecture, Beijing, 100044, P.R. China

Abstract: Considering the problem of gait based gender recognition when gait information can be acquired from multiple views, this paper presents a detailed analysis on how to combine different views and proposes a fusion method derived from Bayesian theory. For feature extraction, a spatio-temporal gait representation is adopted and improved to reduce data redundancies. Then the class separability of each view angle is analyzed by using such features and the gender recognition rate is also computed under every single view. Next, three kinds of fusion scheme are designed to combine these different view angles for a comparison. Experiments are implemented on CASIA Gait Database (Dataset B) and the results demonstrate that the proposed fusion method achieves the superior recognition performance of 97.5% in large datasets.

Keywords: Gait, gender recognition, multi-view fusion, pattern recognition.

1. INTRODUCTION

Gait is the manner of walking as defined in Webster's New Collegiate Dictionary. However, human gait is more than that: it is an identifying feature of a person that is determined by his/her weight, limb length, and habitual posture. Hence, it is reasonable to use gait as a biometric measure to recognize known persons or the gender of an individual. Human walking patterns can contain informative and stylistic variations. Even from point-light displays, people can recognize the gender of a walker [1-5], identify individuals from their gait [3, 6], and estimate dynamic from movement (*e.g.*, estimating the weight of an object being lifted) [7, 8].

For Unlike other traditional biometric sources, such as fingerprints, iris, or hand, gait does not require direct contact and is easy to be acquired at a distance. Therefore, it has the unique characteristic of being unobtrusive and can be observed without requiring the cooperation of the observed person. The specific use of gait in recognition tasks has recently emerged as a very attractive research area due to its applications on surveillance and identification systems. In this paper, we focus on the task of recognizing gender from human walking videos. Actually, human gait is one of the newest biometrics since its development only started when computer memory and processing speed became sufficient to process sequences of image data with a fairly acceptable performance.

Gender recognition is an important visual task for human beings because a typical social category is gender. In [9-11], we can find some gender identification systems based on the voice of speaker. In [12-14], the problem of classifying gender from facial images is described. Furthermore, gender can be recognized from human gait, as shown in [15-17]. It is true that other biometrics sources are also able to be applied in gender recognition.

We know from experience that people often recognize the gender of others by simply observing the way they walk. The fact that we usually look at a walker at a random view angle inspires the idea of analyzing the difference among different views and fusing multi views to enhance the performance of gender recognition. Such fusion can find its application on surveillance, since it is possible and easy to gain gait information from different cameras fixed at different views. Generally speaking, the existing approaches of gait feature extraction attempt to analyze gait sequences and then extract discriminative information from silhouettes.

1.1. Gait Terminology

As is known to all, walking is a periodic process. Its period is termed gait period and there are different stances during a gait period which compose a gait cycle. The cycle of a silhouette sequence is depicted in Fig. (**1**). In a gait cycle, the sub-sequence starting with the left leg moving forward is similar with the one with the right. Therefore, the term half-cycle is used to describe the two sub-cycles.

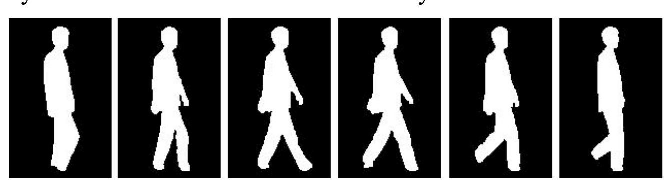

Fig. (1). Different stances in a gait cycle.

1.2. Previous Work

The study of recognizing gender from human gait starts from the attention on moving light displays (MLD), since point-light displays provide an ideal means to study the contribution of motion to the perception of biological move-

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ments, as shown in [18]. The first major experiment was presented in [1] with six walkers (three females, three males) of approximately the same height and weight recorded at a sagittal view. They demonstrate that human observers could classify the gender of the walkers with an average recognition rate of 63%. A further study was presented in [2], where temporal and spatial factors were examined. It was reported that successful gender recognition required exposure to approximately two walking cycles.

Pattern recognition approaches for gender recognition began to be developed in later 1990s. In [19], a two-stage PCA framework was implemented to decompose male and female walking data into an Eigenspace, from which a linear classifier was used for gender recognition. The data consisted of three-dimensional motion-capture trajectories of 40 walkers (20 females, 20 males). And Davis and Gao presented a three-mode expressive-feature model for recognizing gender from point-light displays of walking people [15] with the same data used in [20]. Both of these approaches yielded the same recognition rate of 92.5%.

However, the aforementioned studies can not be applied in surveillance systems because MLD data are captured through attaching retro-reflective markers to the body of the walker. So, video based approaches have been investigated in recent years when the computer speed on processing image sequences became high enough. The paper [20] gives an overall review of the development and current state of automatic gait recognition based on video images. Two main classes of approach have emerged: to either derive the human silhouette or to concentrate on the movement of the torso and the legs. Although gait has received much attention, especially using video, gender identification based on gait was omitted by most of the researchers. Related video based studies can be only found in [16, 17, 21].

In [19], Lee and Grimson developed a gait silhouette appearance representation by proportionally dividing the silhouette into 7 parts. For each part, an ellipse was fitted and features were extracted from these seven ellipses. They applied the gait appearance features to the task of gender classification. On the CMU gait database including 23 men and 2 women, they trained and tested SVM under two conditions: random-sequence test and random-person test. The correct classification rate under former condition was 94% and 84.5% under the other condition.

Yoo *et al.* used a sequential set of 2D stick figures to represent the gait signature [17]. SVM and neural network were employed to carry out gender classification respectively. The overall result was that SVM outperformed neural network in the given task. The best result on the SOTON database including 84 males and 16 females reached 96% under a random-sequence test.

The aforementioned experiments on recognizing gender were implemented using a side view presentation of the walkers to observers. In order to examine the effect of view angle on gender recognition performance, other experiments have been conducted on MLD data. In [4, 19, 22], it was found that a frontal-view presentation of the walker consistently provide better gender recognition results than at a side view. Additionally, using video data, Huang combined the front-view, back-view and side-view presentation of gait to carry out gender classification [21]. In [21], the correct classification rates for the three views are 83%, 85.5% and 85.5% respectively on the CASIA Gait Dataset B (93 males and 31 females) [23]. SUM rule is applied on fusion of the three views and gained a better classification rate 89.5%.

This work aims to find more effective fusion of multi-view gait. The contribution of the paper is two folds. Firstly, we present a detailed analysis of the class separability under different view angles. Secondly, we propose a new fusion method particularly for multi-view gait and the experimental results are encouraging and significant. The rest of this paper is organized as follows. In Section 2, we describe the method which is able to extract gait features at different views. In Section 3, based on the extracted features, the separability is analyzed using Fisher rule. Section 4 introduces the fusion strategies to be compared. Section 5 demonstrates the experimental results. Section 6 concludes the paper.

2. FEATURE EXTRACTION

As described in [20], we may either use a silhouette or design a model to obtain gait features and some approaches even resort to both silhouette and model. But the limitation is that these techniques are based on the data from the 90^0 view. In this paper, the problem is how to generalize them to other views. The model-based approaches usually pay much attention to dynamic variations of a walker or sometimes concentrate on structural body parameters. When view angle changes, such information is hard to be extracted using the same method. In addition, the high computation cost limits the real-time surveillance application of model-based approaches. Hence, we focus our interest on the silhouette-based approaches.

Huang extended Lee's method to 0^0 view and 180^0 view [21]. For each silhouette of a gait video sequence at 90^0 view, Lee proportionally divides the silhouette into 7 parts [16]. Likewise, Huang divides the silhouette from 0^0 and 180^0 view into 5 parts. However, for other views, such as 54^0, 108^0, and so on, it is hard to decide how many parts should be divided.

In paper [24], Yu *et al.* took the well known average silhouette algorithm [25] as an example to evaluate the effect of view angle, clothing and carrying condition on gait recognition. Experiments were conducted on CASIA Gait Dataset B including 11 different view angles from 0^0, 18^0, 36^0 to 180^0, with the angle interval of 18^0. The average silhouette representation is robust to silhouette errors and image noise but it doesn't cover the entire temporal information. We seek to a representation that not only contains enough discriminative features but also has a lower computation cost. The spatio-temporal gait representation proposed in [26] is sensitive to silhouette deformations and robust to spurious pixels. So it is very suitable to analyze the impact of view changing. Therefore, we take this representation into account and make some improvements.

2.1. Preprocessing

Preprocessing is to extract silhouettes of a walking people from a given video sequence and the result of it plays an important role in the following feature extraction work. In this step, we use subtraction to get foreground and morphological filtering to reduce noise after binarization.

We use mean value of multi frames to do background subtraction. Suppose $f_i(x,y)$ is the *i*-th frame of a given video sequence and the mean value of first *k* frame in the given sequence is $\overline{f}_k(x,y)$. μ_k denotes the square deviation of the first *k* frames. As for any other frame in the video sequence, we could extract the foreground with the relationship between differentiate and square deviation as follows:

$$\begin{cases} \| f_i(x,y)-\overline{f}_k(x,y)\| \le \mu_k, & \text{background} \\ \| f_i(x,y)-\overline{f}_k(x,y)\| \ge \mu_k, & \text{foreground} \end{cases} \tag{1}$$

Binarization is difficult because of the varying illumination. Furthermore, due to inaccuracy of differentiate and binarization, there are noises in images. Here we use some morphology filtering methods, such as erosion and dilation, to erase the small spots on binarilized image and to fix discontinuous point on the contour.

2.2. Gait Representation

In [26], for a sequence of silhouette images $b(x,y,t)$ indexed spatially by pixel location (x,y) and temporally by time *t*, the author forms two new 2D images $F_R(x,t)$ and $F_C(y,t)$. Considering the periodicity of gait, we form these two images only from a gait cycle of silhouettes instead of the whole sequence to reduce redundancies. This is our enhancing point for this method. Hence, the largest value of *t* is the number of silhouettes included in one gait cycle, denoted by N_{gait}.

The silhouettes are normalized to the same size and centered in the image before feature extraction. Define a silhouette as $s[i,j]$, $i=0,1,...,M-1$, $j=0,1,...,N-1$, where *M*, *N* denote the number of rows and columns of the silhouette, respectively. Let

$$s[i,j]=\begin{cases} 1 & \text{if}(i,j) \text{ belongs to the foreground} \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Then the horizontal and vertical projection of silhouettes [23] can be expressed as:

$$p_h[i]=\sum_{j=0}^{N-1} s[i,j], \quad i=0,...,M-1 \tag{3}$$

$$p_v[j]=\sum_{i=0}^{M-1} s[i,j], \quad j=0,...,N-1 \tag{4}$$

Consequently, two projection vectors can be defined as follows:

$$H=\{p_h[0],p_h[1],......,p_h[M-1]\} \tag{5}$$

$$V=\{p_v[0],p_v[1],.....,p_v[N-1]\} \tag{6}$$

Here, one gait cycle has N_{gait} silhouettes. Therefore, the aforementioned image $F_R(x,t)$ is formed by N_{gait} H vectors arranged by columns. Likewise, N_{gait} V vectors form the image $F_C(y,t)$. Fig. (**2**) shows these images $F_R(x,t)$ and $F_C(y,t)$ at different view angles from a subject of CASIA Gait Database.

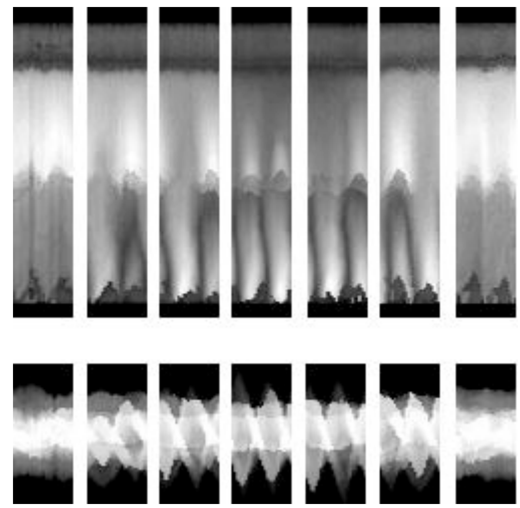


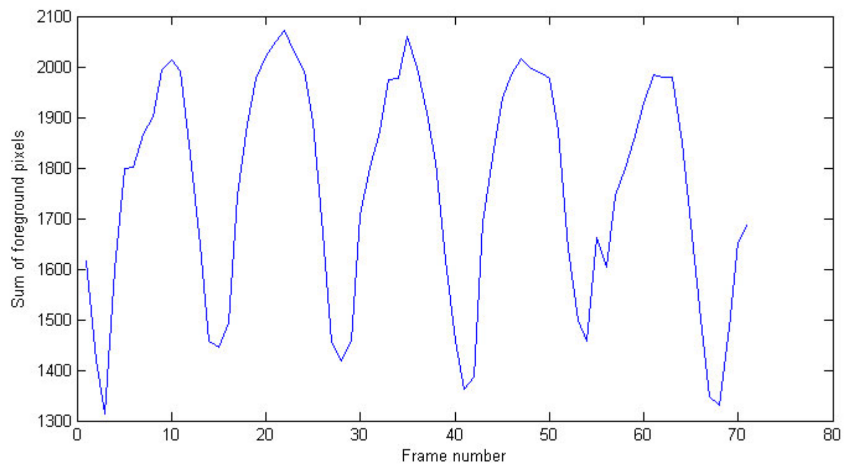
Fig. (2). An example of images F_R and F_C. Columns present different view angles. The top row lists F_R images and the corresponding F_C images are shown in the bottom row.

N_{gait} is calculated through the autocorrelation of the foreground sum signal as proposed in [27]. In order to exploit the periodicity of walking in a gait sequence, we simply count the number of foreground pixels in each silhouette image over time. This number will reach a maximum when the two legs are farthest apart and drop to a minimum when the legs overlap. It is more sensitive to consider the sum of foreground pixels only from the bottom half of the silhouette. Let function $f_s(t)$ denotes this sum and it is noisy in terms of time (see Fig. (**3a**)). Hence, we have to identify the gait cycle length N_{gait} by calculating the autocorrelation $R_w[m]$ (see Fig. (**3b**)) of the signal $w(t)$ which is derived from $f_s(t)$ by subtracting its mean value and dividing by its range. The autocorrelation of $w(t)$ is defined as:

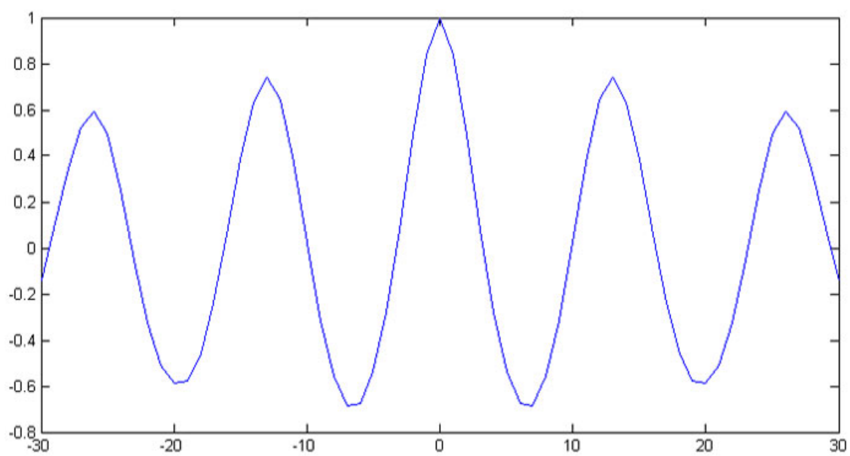
$$R_w[m]=E\{w(t)w(t+m)\} \tag{7}$$

where *E* denotes expectation. The cycle length N_{gait} is easily calculated as the smallest *m*, other than $m=0$, at which there is a local maximum of $R_w[m]$. As shown in Fig. (**3b**), the determination of N_{gait} from the autocorrelation function is unambiguous despite that the original sequence is noisy.

As different people may have different walking period, N_{gait}, we resize all $F_R(x,t)$ and $F_C(y,t)$ images with bicubic interpolation to the same width (the end value of *t i.e.*). Then, PCA is used to retain only the important elements of $F_R(x,t)$ and $F_C(y,t)$ images and we can gain two lower dimension vectors for each pair of $F_R(x,t)$ and $F_C(y,t)$ images. The final feature vector can be produced by simply concatenating these two vectors.



(a)



(b)

Fig. (3). (**a**) Original signal (**b**) Autocorrelation.

3. CLASS SEPARABILITY

We want to know the extent of the separation between male and female sets with the extracted features and further, which view angle can result in a better separation. Since gender classification is a two-class problem, we can resort to the well-known Fisher linear discriminant. Given the within-class scatter matrix S_W and the between-class scatter matrix S_B, the Fisher criterion function can be written as:

$$J(w) = \frac{w^t S_B w}{w^t S_W w} \tag{8}$$

While the vector w maximizes J, we can gain the best separation between two projected sets. The solution for the w that optimizes J is:

$$w = S_W^{-1}(m_1 - m_2) \tag{9}$$

where $m_i (i = 1, 2)$ denotes the sample mean.

The CASIA Gait Database (Dataset B) [22] is used to evaluate the class separability. The gait sequences were captured from 11 viewing angles, including 0^0, 18^0, 36^0, 54^0, 72^0, 90^0, 108^0, 126^0, 144^0, 162^0, and 180^0. This database consists of 124 subjects aged between 20 and 30 years, of which 93 are males and 31 are females. For each view angle, we compute the maximum value of J. The results are listed in Table **1**. Note that we only use the gait sequences of normal walking in CASIA Gait Dataset B.

Table 1. The maximum values of *J*.

View Angle	Maximum of *J*
0^0	5.52
18^0	8.45
36^0	16.23
54^0	15.33
72^0	16.85
90^0	11.64
108^0	15.67
126^0	12.80
144^0	10.95
162^0	7.56
180^0	5.87

From Table **1**, it is easy to draw the conclusion that the 0^0 and 180^0 views have the worst separability. In CASIA Gait Dataset B, the 0^0 view is the frontal view and the walking direction is from right to left. When turning to the side viewing angle, several viewpoints obtain better separation, such as 36^0, 54^0 , 72^0 and 108^0. Other view angles also have better separability than 0^0 and 180^0.

4. FUSION STRATEGIES

The aim of this work is to present the advantage of multi-view fusion with practical experiments for gait based gender recognition. Every view will act as a classifier independently. Relying on the results of classifiers, we concentrate on the fusion of decision level. Lin *et al.* [28] demonstrate that multi-biometric integration does indeed result in a consistent performance improvement. So does multiple classifiers from the same biometrics.

As shown in [29], fusion on decision level is that each classifier makes its own classification and votes for the final decision [30-32]. The popular vote rules include rank sum and majority vote. In this section, we will introduce three fusion rules on the decision level, including two popular rules and a proposed method.

There exist many ways to combine classifier decisions, and there is nearly no limit in inventing more or less sophisticated combination rules. As many previous studies, we are interested in general fusion schemes such as majority voting and weighted majority voting rules. Particularly, we design a fusion strategy for our problem based on Bayesian inference.

4.1. Voting Rule

This strategy is motivated by the way humans are making decisions, especially when there is a group of people involved in the decision process. Each classifier is in the position of a human expert with one vote. The resulting class is determined by the majority of votes. Let $v(n)$ denote the number of classifiers with class n on the first rank:

$$v(n) = \sum_{n=n_1} C_i, n_1 \in R_C \tag{10}$$

where n_1 is the first rank of the i-th classifier C_i. The decision rule of voting is defined as:

$$R_K = \{n_i \mid v(n_i) = \max\{v(n_j), n_j \in S\}\} \tag{11}$$

A rejection will be returned, if $|S| \neq 1$. In this case either no class fulfills the criteria (S is an empty set) or more than one class has the same number of votes (S has several elements) [33].

4.2. Weighted Voting Rule

The weighted voting method is no more than a variant of voting strategy, where each expert has its individual weight.

$$v(n) = \sum_{n=n_1} wC_i, n_1 \in R_C \tag{12}$$

The weights w need to be defined before the fusion process is applied. In our experiments, we take the maximum values of J (see Table **1**) as the weights for different views.

4.3. Bayes Combination Rule

The Bayesian theory is known to all. Here we propose a fusion rule based on this theory for our case. Given m possible classes $\omega_1,...,\omega_m$, we assume that both the prior probabilities $P(\omega_j)$ and the conditional densities $p(x \mid \omega_j)$ for an observation x are known. Bayes formula shows how to calculate the posteriori probability:

$$P(\omega_j \mid x) = \frac{p(x \mid \omega_j)P(\omega_j)}{\sum_{k=1}^{m} p(x \mid \omega_k)P(\omega_k)} \tag{13}$$

This theorem can be used for the inference of the joint probability of the input classifiers. In our case, we intend to combine the results from multiple classifiers on decision level. For a person, there are six walking sequences at one view in CASIA Gait Database. We use the voting rule to decide the person's gender, assigning one vote to each sequence. Let $P_m(v_{ij})$ be the possibility of the i-th person being classified as male from the j-th classifier. $P_m(v_{ij})$ can be defined as:

$$P_m(v_{ij}) = \frac{N_m}{N_t} \tag{14}$$

where N_m denotes the number of votes on male and N_t is the number of total votes which is 6 in CASIA Gait Database. Likewise, $P_f(v_{ij})$ denotes the possibility being classified as female. Then, the fusion can result in the possibility $p_m(w_i)$ of recognizing a walker as a male with the following expression:

$$p_m(w_i) = \frac{P(m)\sum_j P_m(v_{ij})}{P(m)\sum_j P_m(v_{ij}) + P(f)\sum_j P_f(v_{ij})} \tag{15}$$

where $P(m)$ is the percent that males take up in the database and $P(f)$ is the percent of females. They can be looked as the prior probabilities of the two classes.

5. EXPERIMENTAL RESULTS

From Table **1**, we can find that the maximum J values from the view angles more than 90^0 are smaller than those corresponding views less than 90^0. Therefore, we first investigate the fusion of the five views more than 90^0. Then we carry out experiments by combining all the eleven views. The aforementioned three fusion schemes are applied in these two sets of experiments respectively.

As mentioned above, we use CASIA Gait Dataset B in our experiments. This database consists of 93 male subjects and 31 female subjects. Each subject walked naturally along a straight line six times, captured by 11 cameras simultaneously at different viewing points. So, the total number of video sequences used in our experiments is 8184 ($124 \times 6 \times 11$).

To evaluate the generalization ability of fusion algorithms, we adopted a 5-fold cross-validation test scheme in all recognition experiments. The CASIA Gait Dataset B is

Table 2. Results of classification under linear kernel.

View Angle	CRR
0^0	78.7%
18^0	83.4%
36^0	90.3%
54^0	91.7%
72^0	92.6%
90^0	90.3%
108^0	91.7%
126^0	88.3%
144^0	84.0%
162^0	83.1%
180^0	82.3%

Table 3. Results of five-view fusion.

Fusion Scheme	CRR after Fusion
Majority voting	95.0%
Weighted majority voting	97.0%
Bayes combination rule	93.7%

Table 4. Results of all views fusion.

Fusion Scheme	CRR after Fusion
Majority voting	96.7%
Weighted majority voting	97.1%
Bayes combination rule	97.5%

randomly divided into five groups with roughly equal (female and male) subjects. Four of them are used for training and the left one for testing. The process was repeated five times for each group in turn to be tested. The average recognition rates are reported in our experiments. We use support vector machine (SVM) as the classifier tool in the experiments for each single view. The three fusion strategies mentioned above are performed on the decision level in the fusion experiments.

The correct recognition rates (CRR) for every viewing angle are listed in Table **2**. We ran SVM with different kernels among which linear kernel performs the best. The fusion results can be found in Table **3** and **4**.

According to the results shown in Table **2-4**, the multi-view fusion leads to an obvious improvement on CRR when compared with single view based rates. The proposed fusion scheme Bayes combination rule yields better result than common voting rules. Also, we can see from Table **3** and **4** that fusing more views perform even better for gait based gender recognition.

CONCLUSION

In this work, we investigated the effect of different view angle on gait-based gender recognition and integrated multiple views to improve the correct recognition rates. Both the analysis of class separability and the results of our classification experiments demonstrate the obvious difference in the contribution for gait-based gender classification when the view angle changes. We find that the 0^0 view and 180^0 view perform the worst and the oblique view in front of a person is most helpful when recognizing gender. The fusion experiments showed that the more view information we combine, the better recognition rate we will achieve.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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