Gabor-based Facial Image Sequential Pattern Mining for Human Fatigue Monitoring

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Abstract

Fatigue is the main factor to cause traffic accidents. Based on survey of existed fatigue detection methods, a new method for extracting characteristics of Human face based on Gabor translation is proposed in this paper, and based on which, by combing with the frequent patterns mining, a new fatigue detection method for vehicle drivers based on the Human face image sequences is proposed. Simulation results show that the newly proposed algorithm has better fatigue detection performance for identification of vehicle drivers than the existed method based on single face image.

Keywords: *Fatigue Detection, Gabor Translation, Face Image Sequence*

1. Introduction

Currently, there are lots of methods proposed for fatigue detection on the basis of facial features of drivers[1-2]. For example, Hertmann[3]utilized the eye gazing data to detect the driver's physical and psychological condition according to the changes of the pupil diameter. Experimental results show that Eye-gaze data appears to contain information about micro sleep events several seconds before the real event takes place, and the pupil diameter will show a slowly fluctuating pattern correlated to no change in the eye-gaze coordinates. But closer to the micro sleep event the pupil diameter will decrease and the eye-gaze coordinates will drift rapidly until the eyes are totally closed. In addition, T. Ito, S. Mita, K. Kozuka, T. Nakano, and Nakano Yamamoto[4] utilized the frequency of eye blink to detect fatigue from the moving images, and Wang[5] utilized the wavelet translation to extract the eye features after detecting the face region, and then, utilized neural networks to carry the final fatigue detection. All these works obtained good performances to a certain extent.

When a driver is in normal, talking or dozing state, opening degree of his/her mouth will be quite different. According to this fact, Chu[6] used the Fisher classifier to extract the mouth shape and position, and then, used the mouth region's geometry character as the feature value, and put all of these features together to make up an eigenvector as the input of a three-level Bp network, thus, three different spirit states related to normal, talking and dozing state are obtained.

In these above methods, since the eye and mouth state are considered independently, and the whole face is not considered as a union to detect fatigue, thus, the recognition rate of these above methods are not very high. So there are some researchers proposed a fatigue detection method based on the whole facial features. The most representative methods include Gabor and Adaboost based method[7]、dynamic Bayes network based method[8] and lasting time of eye closure and yawning patterns based method [9]. But in these methods, only a single facial image is used to judge the fatigue of drivers and the relationship between the former or the behind frames are not considered, thus, the detect rate of these methods are not very high also.

Thus, we propose a driver fatigue detection method based on the face image sequence model, in which, it is not a single facial image but a face image sequence is considered to judge the fatigue of drivers. In the newly proposed method, the facial image sequence will be represented as the Gabor feature sequence through Gabor translation, and then, the classification algorithm will be used for fatigue detection of the Human face image sequence. Simulation results show that the newly proposed algorithm has better fatigue detection performance for identification of vehicle drivers than the existed method based on single face image.

The organization of the paper is as follows. Section 2 illustrates our new method for fatigue detection, section 3 includes the experimental results, and section 4 draws the conclusion.

2. Gabor-based human fatigue monitoring model

2.1. Gabor wavelets

The kernel function of two-dimensional Gabor wavelets can be defined as:

$$g_{v,u}(x,y)=\frac{\|k\|^2}{\sigma}\exp\left(-\frac{\|k\|^2(x^2+y^2)}{2\sigma^2}\right)(\exp\left(ik\cdot\begin{pmatrix}x\\y\end{pmatrix}\right))-\exp(-\frac{\sigma^2}{2})) \quad (1)$$

Where:

k= $k=\begin{pmatrix}k_x\\k_y\end{pmatrix}=\begin{pmatrix}k_v\cos\varphi_u\\k_v\sin\varphi_u\end{pmatrix}$, $k_v=2^{-\frac{v+2}{2}}\pi$, $\phi_u=u\frac{\pi}{k}$, $\sigma=\sqrt{2}\pi$. And i is the complex operator, u and v determine the orientations and frequencies (scale) of the Gabor wavelets respectively, K is the total number of orientations, and ||.|| denotes the norm operator.

2.2. Features representation for a facial image sequence

For an image with the grey-scale distribution of I(x,y), at a given pixel position (x,y), the Gabor expression of the image in direction u at scale v can be defined as:

$$G_{v,u}(x,y)=\iint I(\varepsilon,\eta)g_{u,v}(x-\varepsilon,y-\eta)d\varepsilon d\eta \quad (2)$$

Where $u\in[0,1,\ldots,D-1]$, $v\in[0,1,\ldots,S-1]$.

Before Gabor wavelets are applied to each facial image in the facial image sequence, original facial images are preprocessed so that they are aligned in a predefined way. The alignment and cropping are done according to the eye centers from face detection.

Supposing that the width and height of each preprocessed facial image are W and H, the width and height of the sampling window are Lx and Ly, and the horizontal and vertical overlap of the sampling window are P_x and P_y respectively, then, the number of samples in the horizontal and vertical directions can be computed as:

$$T_0=\left\lfloor\frac{H-L_y}{L_y-P_y}\right\rfloor+1 \quad (3)$$

$$T_1=\left\lfloor\frac{W-L_x}{L_x-P_x}\right\rfloor+1 \quad (4)$$

Where T_0 denotes the number of samples in the vertical direction, T_1 denotes the number of samples in the horizontal direction, and $\lfloor\ \rfloor$operator means to round down to the nearest integer.

According to the above method, a facial image Ii can be divided into T_0*T_1 (=T) different local sub-images $\{L_{i,r}, r\in[0,1,\ldots,T-1]\}$. For each local sub-image $L_{i,r}$, selecting its center point $(x_{i,r}, y_{i,r})$ as the feature point of the whole local sub-image, then, based on the formula (2), the local sub-image Li,r in direction u at scale v can be represented by a complex value Gi,v,u,r (xi,r, yi,r). For convenience, let:

$$T_{i,v,u,r}\ (x_r,\ y_r)= \begin{cases} 1: If G_{i,v,u,r}\left(x_{i,r}\ y_{i,r}\right) > 0 \\ 0: If G_{i,v,u,r}\left(x_{i,r},\ y_{i,r}\right) \le 0 \end{cases} \tag{5}$$

Then, a facial image Ii in direction u at scale v can be represented by a T dimensional 0-1 feature vector Vi,v,u as:

$$V_{i,v,u}=(T_{i,v,u,0}(x_{i,0},\ y_{i,0}),\ T_{i,v,u,1}\ (x_{i,1},\ y_{i,1}),\ldots,\ T_{i,v,u,T-1}\ (x_{i,T-1},\ y_{i,T-1})) \tag{6}$$

Let:

$$D_{i,v,r}= \begin{cases} 1: If \dfrac{\sum_{u=0}^{D-1} T_{i,v,u,r}\ \left(x_{i,r} y_{i,r}\right)}{D} > 0.5 \\ 0: If \dfrac{\sum_{u=0}^{D-1} T_{i,v,u,r}\left(x_{i,r} y_{i,r}\right)}{D} \le 0.5 \end{cases} \tag{7}$$

Then, a facial image Ii at scale v can be represented by a T dimensional 0-1 feature vector Vi,v as:

$$V_{i,v}=(D_{i,v,0},\ D_{i,v,1},\ldots,D_{i,v,T-1}) \tag{8}$$

Let:

$$X_{i,v}=\{\ v, \sum_{r=0}^{T-1} D_{i,v,r} * 2^r\ \} \tag{9}$$

Then, a facial image Ii can be represented by a (S-1)-dimensional feature vector I_i^v as:

$$I_i^v = (\{0, X_{i,0}\}, \{1,\ X_{i,1}\}, \ldots, \{S\text{-}1, X_{i,S\text{-}1}\}) \tag{10}$$

Therefore, for a given facial image sequence S=<I0, I1,…,In-1>, we can represent it as a feature vector sequence:

$$S^V = < I_0^v, I_1^v, \ldots,\ I_{n-1}^v > \tag{11}$$

3. Fatigue sequential pattern mining in the training set

3.1. Sequential-pattern mining

Sequential pattern mining, which discovers frequent subsequences as patterns in a sequence database, is an important data mining problem with broad applications, including the analysis of customer purchase patterns or Web access patterns, the analysis of sequencing or time-related processes such as scientific experiments, natural disasters, and disease treatments, the analysis of DNA sequences, etc.

The sequential pattern mining problem was: Given a set of sequences, where each sequence consists of a list of elements and each element consists of a set of items, and given a user-specified minimum support threshold, sequential pattern mining is to find all frequent subsequences, i.e., the subsequences whose occurrence frequency in the set of sequences is no less than minimum support threshold.

According to the above description, the problem of sequential pattern mining can be defined as follows:

Let I={i_1,i_2,…,i_n} be a set of all items. An itemset is a subset of items. A sequence is an ordered list of itemsets. A sequence s is denoted by <s_1,s_2,…,s_l>, where s_j is an itemset, and s_j is also called an element of the sequence, and denoted as (x_1,x_2,…,x_m), where xk is an item. An item can occur at most once in an element of a sequence, but can occur multiple times in different elements of a sequence. The number of instances of items in a sequence is called the length of the sequence. A sequence s= <s_1,s_2,…,s_l> is called a subsequence of another sequence t= <t_1,t_2,…,t_m> and t is a supersequence of s, denoted as s ⊆ t, if there exist integers 1≤ j_1≤j_2≤…≤j_l≤m such that: $s_1 \subseteq t_{j_1}$, $s_2 \subseteq t_{j_2}$,…, $s_l \subseteq t_{j_l}$.

A sequence database $\mathcal{S}$ is a set of couples <s_{id}, s>, where s is a sequence and s_{id} represent its sequence id, and a couple <sid, s> in Γ is said to contain a sequence α, if α is a subsequence of s (α ⊆ s). The support of a sequence α in the sequence database $\mathcal{S}$ is the number of couples in the database containing α, i.e.:

$$\mathrm{support}(\alpha, \Gamma) = |\{<s_{id}, s>|\ (<s_{id}, s> \in \Gamma) \wedge (\alpha \subseteq s)\}| \tag{12}$$

Where |{A}| means the number of instances in the set {A}.

Given a positive integer min_support as the support threshold, a sequence α is called a sequential pattern in sequence database Γ, if support(α) ≥ min_support. A sequential pattern with length l is called an l- sequential-pattern.

On the basis of the above definitions, then, the sequential pattern mining problem can be stated as follows:

Given a positive integer min_support as the support threshold, sequential pattern mining is to find the complete set of sequential patterns in the sequence database Γ.

3.2. Fatigue-sequential-pattern mining

Based on the features representation method for a facial image sequence proposed in the above section 2.2, it is obvious that for each fatigue image sequence S_t = <I_{t-m_t+1}, I_{t-m_t+2},…,I_t> in the training set, we can represent each facial image Ii ∈ St as a itemset I_i^v = {{0,$X_{i,0}$},{1, $X_{i,1}$},…,{S-1,$X_{i,S-1}$}} according to the formula (10), in which each {j, $X_{i,j}$}∈ I_i^v is called an item. Hence, the fatigue image sequence St can be represented as a fatigue feature sequence S_t^v=<I_0^v, I_1^v,…, $I_{m_t-1}^v$> according to the formula (11), in which each I_i^v ∈ S_t^v is called a transaction.

Let S_F^v = { S_1^v, S_2^v,…, S_M^v }be all the fatigue features sequences obtained from all the fatigue image sequences in the training database, and for simplicity, supposing that there is a transaction-time associated with each transaction in S_j^v, and at the same time, the transaction-times associated with different transactions are different. For each sequence S_t^v=<I_0^v, I_1^v,…, $I_{m_t-1}^v$>, let the transaction-times associated with its transactions I_0^v, I_1^v,…, $I_{m_t-1}^v$ be T_0, T_1,…, T_{m_t-1} respectively, and T_t^v = max{T_0, T_1,…, T_{m_t-1}}, then we select T_t^v as the sequence id of the sequence S_t^v. Thus, it is obvious that the fatigue sequence database Γ for training can be represented as the set of couples <T_t^v, S_t^v>.

According to the above descriptions and the definition of the problem of sequential pattern mining introduced in the section 2.3.1, now we can conclude the problem of fatigue-sequential-pattern mining as:

Given a positive integer min_support as the support threshold, fatigue sequential patterns mining is to find the complete set of fatigue sequential patterns in the fatigue sequence database Γ, where the support of a fatigue image sequence α in the fatigue sequence database Γ is the number of couples in the database containing α, i.e.:

$$\text{support}(\alpha, \Gamma) = |\{ <T_t^v, S_t^v> | (<T_t^v, S_t^v> \in \Gamma) \wedge (\alpha \subseteq S_t^v) \tag{13}$$

Where, the fatigue sequence α is called a fatigue sequential pattern in the fatigue sequence databaseΓ, if support(α, Γ) ≥ min_support. A fatigue sequential pattern with length l is called an l-fatigue-sequential-pattern.

In addition, we define the frequency of a fatigue sequence α in Γ as the probability of α occurring in a couple $<T_t^v, S_t^v> \in \Gamma$, i.e.:

$$\text{frequency}(\alpha, \Gamma) = \text{support}(\alpha, \Gamma)/|\Gamma| \tag{14}$$

Where |Γ| denotes the number of couples in Γ.

Therefore, when using frequency of a sequence instead of its support as the threshold, a sequence is called frequent if its support is no less than a given relative minimal frequency threshold σ (0 ≤ σ ≤1).

For a fatigue sequential pattern $a=<a_1,a_2,\ldots,a_l>$, let the itemset $\Psi_a=a_1 \cup a_2 \cup \ldots \cup a_l$ be α's projected itemset, then, based on the Apriori principle: any super-pattern of an infrequent pattern cannot be frequent (Jian Pei, Jiawei Han, et al. 2004), our new fatigue sequential patterns mining algorithm can be outlined as follows:

Input: The set of fatigue image sequences for training and a given support threshold *min_support*;
Output: Maximum fatigue sequential patterns.
Step1: Constructing the fatigue sequence database Γ.
Step1.1: Representing each fatigue image sequence $S_t = <I_{t-m_t+1}, I_{t-m_t+2}, \ldots, I_t>$ as a fatigue feature sequence $S_t^v=<I_0^v, I_1^v, \ldots, I_{m_t-1}^v>$
Step1.2: Representing each fatigue feature sequence S_t^v as a couple $<T_t^v, S_t^v>$ by appending the sequence id to S_t^v. Thus, the fatigue sequence database $\mathcal{S}$ can be represented as the set of couples $<T_t^v, S_t^v>$.
Step2: Scanning the fatigue sequence database $\mathcal{S}$ to find out all of the frequent items (i.e., 1-sequential-patterns) $x_1,x_2,\ldots,x_n$, and at the same time, collect the support support_i for each 1-sequential-pattern x_i, and thereafter, forming the sets of 1-sequential-patterns $L_1=<x_1,x_2,\ldots,x_n>$, here, the 1-sequential-patterns $x_1,x_2,\ldots,x_n$ are listed in support descending order, i.e., let $\text{support}_1,\text{support}_2,\ldots,\text{support}_n$ be the supports of $x_1,x_2,\ldots,x_n$ respectively, there is $\text{support}_1 \geq \text{support}_2 \geq \ldots \geq \text{support}_n$.
Step3: FOR (k=2; $L_{k-1} \neq \Phi$; k++) DO BEGIN
Step4: C_k= fatigue-sequential-patterns-candidates- generate(L_{k-1})
Step5: For each $<T_t^v, S_t^v> \in \Gamma$ DO
Step6: Increment the count of all candidates in C_k that are subsequences of S_t^v
Step7: L_k=Candidates in C_k with the support no less than *min_support*.
Step8: END
Step9: ANSWER=Maximal sequences in $\bigcup_k L_k$.

In the above fatigue sequential patterns mining algorithm, the sub-algorithm fatigue-sequential-patterns- candidates-generate(L_{k-1}) can be illustrated as follows:

Step1(Join Phase): Generating the candidate k-sequential-patterns by joining $L_{k-1}$with L_{k-1} as follows:

For two (k-1)-fatigue-sequential-patterns s_1 and s_2 in L_{k-1}, if the subsequence obtained by dropping the first item of s_1 is the same as the subsequence obtained by dropping the last item of s_2, then the two sequences s_1 and s_2 are called to be able to be joined together. And hence, a new candidate k-fatigue-sequential-pattern can be generated by joining s_1 with s_2, i.e., by extending the sequence s_1 with the last item in s_2. Since the added item (i.e., the last item in s_2) will be a separate element in s_1 if it is a separate element in s_2, or a part of the last element of s_1 otherwise, then, it is necessary to add the item in s_2 both as a part of an itemset and a separate element in s_1 when joining $L_{k-1}$with L_{k-1}.

Step2(Prune Phase): Deleting all these candidate *k*-fatigue-sequential-patterns that have a contiguous (*k*-1)-sequence whose support count is less than the given support threshold *min_support*.

4. Human fatigue monitoring algorithm

4.1. New algorithm

Supposing that the facial image stream obtained through continuous monitoring is I1,I2,…,Ij,… we define the time interval ΔT as the sliding time window, then, we can divide the continuous facial image stream into discrete segments (i.e., sequences) with time interval ΔT. For a given time interval ΔT, supposing that there are mt images included in the sliding time window, then, we can generate a testing image sequence T_t=< I_{t-m_t+1}, I_{t-m_t+2},…,I_t>during the given time interval ΔT. It is obvious that our purpose is to determine that whether the testing image sequence T_t is a fatigue sequential pattern. If T_t is a fatigue sequential pattern, then, we can declare that the monitored people is tired, otherwise, we can announce that the monitored people is not tired yet.

Supposing that the set of mined fatigue-sequential-patterns through the new fatigue sequential patterns mining algorithm given previously is Ψf, then, based on the above descriptions, our new human fatigue monitoring algorithm can be illustrated as follows:

Input: facial image stream continuously collected by the monitor Θ

Output: fatigue or not

Step1: When a new facial image I_{new} is collected by the monitor, constructing a facial image sequence S_c=<I_1,I_2,…,I_n> through the sliding time window, where I_n= I_{new}, I_j is the previous facial image of I_{j+1} in the facial image stream Θ for $j\in[2,n-1]$, and the time interval between I_1 and I_n is ΔT.

Step2: Representing the facial image sequence S_c as a facial feature sequence S_t^v=< I_0^v, I_1^v,…, $I_{m_t-1}^v$>.

Step3: FOR EACH fatigue-sequential-pattern α ∈ Ψ_f DO

Step4: IF α is a subsequence of S_t^v, then, outputting that the monitored people is tired and triggering an alert.

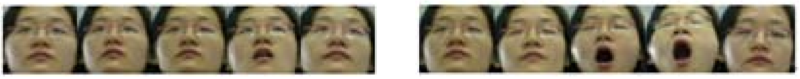
Step5: END

Step6: RETURN to Step1.

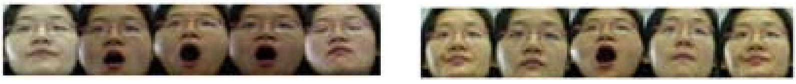
4.2. Algorithm performance analysis

According to the description given in above sections, it is easy to know that our method is quite different from those existed methods. In our newly proposed method, fatigue detection is based on facial image sequence, but in those existed methods, fatigue detection is based on the current single facial image only. Thus, it is obvious that our newly proposed method is more reasonable since a single facial expression will not be efficient for determining whether a person is tired or not at most time.

For the lack of public fatigue detection video database, we collected the video of a driver in different time of day, different illumination and different pose through video sensor network, The video lasts for a few hours, and the resolution is 320*240. The experimental environment is: Intel double kernel 2.0 GHz CPU, 2G memory. After the video is obtained, we first sample the video to form facial image sequences, the following figure 1 gives four kinds of different facial image sequences extracted from the video after face monitoring and normalization.



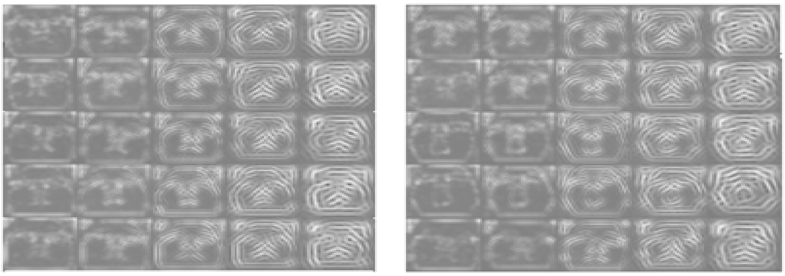
(*a*)Normal facial image sequence (*b*) Fatigue facial image sequence



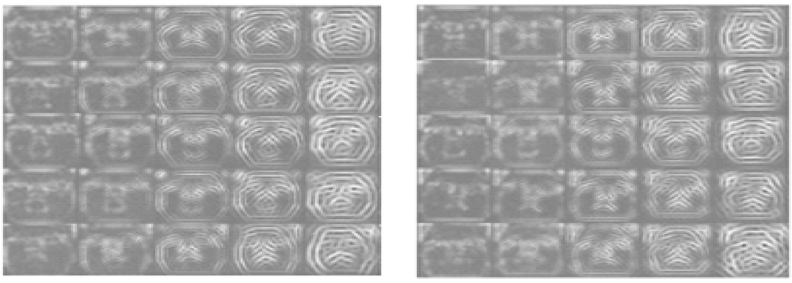
(*c*) Fatigue facial image sequence (*d*) Pseudo-fatigue facial image sequence

Figure 1. Different facial image sequences

As for each of the different facial image sequences extracted from the video, then we can obtain its Gabor feature vector by utilizing Gabor translation. The following figure 2 illustrates the Gabor feature image sequences of the four kinds of different facial image sequences given in the figure 1.



(*a*)Normal Gabor feature image sequence (*b*) Fatigue Gabor feature image sequence



(*c*) Fatigue Gabor feature image sequence *(d)* Pseudo-fatigue Gabor feature image sequence

Figure 2. Gabor feature image sequences for different facial image sequences given in figure 1

In the experiment, we use the fused Gabor feature vectors of 500 fatigue facial image sequences for fatigue sequential pattern mining. And then, the mined fatigue sequential patterns are used to carry fatigue detection to all kinds of video sequences. We compared it with the method proposed by [7]. The results are show in table 1, in which the items used are calculated as follows:

(1) The correct rate of fatigue detection (Correct detection rate) = the number of fatigue sequences detected correctly / the number of real fatigue sequences.

(2) The Error rate of fatigue detection (Error detection rate) = the number of error detected fatigue sequences / the number of real fatigue sequences.

Table1. the comparison of the fatigue detection rates

Method	*Correct detection rate*	*Error detection rate*
Our method	99.2%	0.02%
Method proposed by [7]	98.6%	1.28%

From the above table 1, we can draw the conclusion that the correct rate of fatigue detection of the method proposed by [7] is closer to that of our proposed method, but the error detected rate is much higher than that of ours. From analysis, it is easy to know the reason is that the method proposed by [7] just used the single image to carry fatigue detection only, so it will classify all the Pseudo-fatigue sequences into fatigue models. But in our method, seldom will the pseudo-fatigue sequences be classified into fatigue models. Thus, the error detection rate of our method will be very low.

5. Conclusion

A new method for fatigue detection based on Gabor translation and human facial image sequence is proposed in this paper, in which, the Gabor translation is used to extract the feature sequences of the human facial image sequences first, and then, the frequent patterns mining algorithm is used to mine the patterns of fatigue facial image sequences, finally, during the recognition stage, the classification algorithm will be used for fatigue detection of the Human face image sequences. Simulation results show that the newly proposed algorithm has good fatigue detection performance.

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7. References

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