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# 基于CLSTM的步态分类方法

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**摘要:**步态分类在人体运动能量消耗评估等应用中具有重要意义,提高分类精度和降低对统计特征的依赖是步态分类的研究热点。采用传统的步态分类方法提取的步态特征用于细分化步态时不能得到较好的效果。考虑到步态的连续性和不同轴之间信号的相关性,本文提出了基于CLSTM的步态分类方法:采用卷积神经网络(CNN)操作,通过计算多轴步态数据提取步态特征;基于长短期记忆(LSTM)构建步态时间序列模型,学习步态特征图时间维度上的长期依赖性。基于USC-HAD数据集的实验结果表明,用此方法提取了步态序列特征,很好地利用了步态时间序列特点,提升了11种步态的分类精度。

**关键词:**步态分类;信号相关性;卷积神经网络;LSTM
**中图分类号:**TP391.41 **文献标志码:**A

# A Gait Pattern Classification Method Based on CLSTM

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**Abstract:** Gait classification is an effective method for the assessment of human motion energy consumption, in which the key issue is to improve its classification accuracy and decrease the dependence on statistic features. Aiming at the shortcoming of the traditional gait classification methods in classifying subdivided gaits, this paper proposes a CLSTM method by considering the continuity of the gait and the signal correlation among different axes. By means of CNN convolution operation, this proposed method can extract the gait features by calculating the gait data among multi-axis. Besides, the present method utilizes the LSTM-based gait time series model to learn long-term dependent relation on gait features in the time dimension. Finally, it is illustrated via experiment on USC-HAR datasets that the proposed method can extract gait sequence features and effectively utilize the characteristics of gait time-series to raise classification accuracy in 11 gaits pattern.

**Key words:** gait classification; signal correlation; convolution neural network; LSTM

, [1-3], [4] 11 ,
、 。 [1,5]
、 。 , , [6],
, , ,

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。 [7-8] ，
， ， ， ， $Z$
， ，
， 。 [9] $36\times N$ ：

$$Y=[g_{x,i},g_{y,i},g_{z,i},a_{x,i},a_{y,i},a_{z,i},l_{x,i},l_{y,i},l_{z,i},g_{x,i},g_{z,i},a_{y,i},l_{x,i},l_{z,i},\cdots,a_{z,i}]^{\mathrm{T}} \quad (2)$$

， ， 。 CNN
， ， 。 。

、 。 [8] (DNN) ， [7]。 [10] CNN LSTM ，CNN ，LSTM ， 。 ， CLSTM 。

，
，CNN
，
。CNN 、 ， ，
， ， 、
。LSTM
， ，
， ， 。 USC-HAD[4]
，
，
， 。

## 1

### 步态信号的表示

， ， [6-11]。

$Gyro=[g_{x,i},g_{y,i},g_{z,i}]^{\mathrm{T}}$，

$\mathbf{Acc}=[a_{x,i},a_{y,i},a_{z,i}]^{\mathrm{T}}$，

( ) $\Delta\mathbf{Acc}=[l_{x,i},l_{y,i},l_{z,i}]^{\mathrm{T}}$，$i=1,2,3,\cdots,N$，$N$ 。 $9\times N$ ：

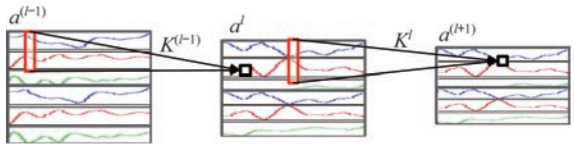
$$Z=\begin{bmatrix} Gyro \\ \mathbf{Acc} \\ \Delta\mathbf{Acc} \end{bmatrix} \quad (1)$$

### 1.2 基于 CNN 卷积的步态特征提取

CNN [12]。 1.1 $36\times N$ CNN ， ， 、 ， ， 。
，
。
， ， ， 1 。 $a_j^l(\tau)$ $l$ 、 $j$ ：

$$a_j^{(l+1)}(\tau)=\sigma\Big(b_j^l+\sum_{f=1}^{F^l}\sum_{p=1}^{P^l}K_{jf}^l(p)a_f^l(\tau-p)\Big) \quad (3)$$

：$\sigma$ ReLU，$\sigma(x)=\max(0,x)$；$b_j^l$ $j$ ；$F^l$ $l$ ；$K_{jf}^l$ $l$ $f$ $(l+1)$ $j$ ；$P^l$ $l$ 。




1

Fig 1 Gait features extraction process

## 2 CLSTM

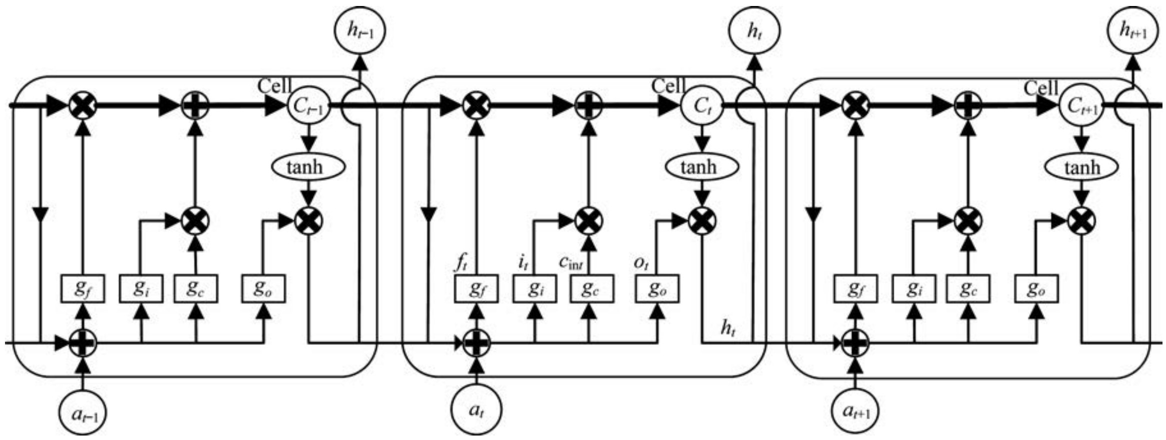
### 2.1 概述

， HMM、SVM CNN ，
，
， 。 LSTM
，
， 、

(Cell State), 。 , LSTM 、 、

## 2.2 基于 的循环神经网络模型

, [1-2] CNN , , 。 , LSTM , , ; , , , , 。 LSTM 2 。




2 LSTM

Fig. 2 Schematic diagram of LSTM model for gaits classification

LSTM $(a_1, a_2, \cdots, a_T)$ $t-1$ $h_{t-1}$, $(h_1, h_2, \cdots, h_T)$。LSTM :

(1) $t$ “ ” $c_{\mathrm{in}\,t}$ $i_t$。

$$i_t = g_i(W_{ai} a_t + W_{hi} h_{t-1} + W_{ci} c_{t-1} + b_i) \quad (4)$$

$$c_{\mathrm{in}\,t} = g_c(W_{ac} a_t + W_{hc} h_{t-1} + b_{c_{\mathrm{in}}}) \quad (5)$$

:$g_i$, $g_c$ sigmoid tanh ;$c_{t-1}$ $t-1$ ;$W_{ai}$, $W_{hi}$, $W_{ci}$ $a$、 $h$ $c$ $i$ ;$W_{ac}$, $W_{hc}$ $a$ $h$ $c$ ;$b_i$, $b_{c_{\mathrm{in}}}$ 。 (BPTT)[13] 。$i_t$ [0 1], $t$ $c_{\mathrm{in}\,t}$ $t$ $c_t$ 。

(2) $f_t$。

$$f_t = g_f(W_{af} a_t + W_{hf} h_{t-1} + W_{cf} c_{t-1} + B_f) \quad (6)$$

:$g_f$ sigmoid ;$W_{af}$, $W_{hf}$, $W_{cf}$ $a$、 $h$ $c$ $f$ ;$b_f$ 。$f_t$ [0 1], , , $t$ $t-1$ 。

(3) (Cell state) 。 $f_t$ $i_t$ $c_t$ ,

$$c_t = f_t \cdot c_{t-1} + i_t \cdot c_{\mathrm{in}\,t} \quad (7)$$

:$c_t$ $t$ $c_{\mathrm{in}\,t}$ $t-1$ $c_{t-1}$ ;$f_t \cdot c_{t-1}$ $t$ $c_t$ $c_{t-1}$ ,$f_t$ , $c_{t-1}$ $c_t$;$i_t \cdot c_{\mathrm{in}\,t}$ $t$ $c_{\mathrm{in}\,t}$ $c_t$ ,$i_t$ , $c_{\mathrm{in}\,t}$ $c_t$, , $c_t$。

(4) $h_t$、 $o_t$。

$$o_t = g_o(W_{ao} x_t + W_{ho} h_{t-1} + W_{co} c_t + b_o) \quad (8)$$

$$h_t = o_t \cdot \tanh(c_t) \quad (9)$$

:$g_o$ sigmoid ;$W_{ao}$、$W_{ho}$、$W_{co}$ $a$、 $h$、 $c$ $o$ ;$b_o$ ;$h_t$ $o_t$ $c_t$ , $t$ 。

## 2.3 基于 的步态分类方法

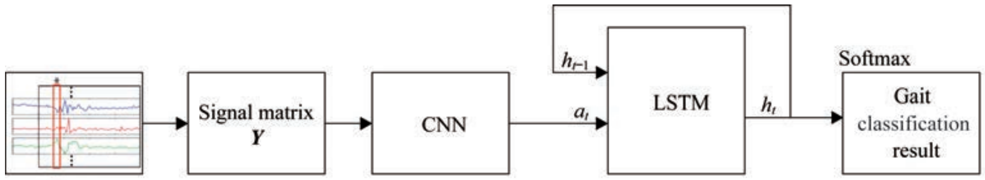
CLSTM 3 , 、CNN 、LSTM Softmax 。 :

(1) 1.1 , 2 $36 \times N$ $Y$。

(2) (3) 4 $5 \times 5$ $P^l$

, 64 ,
[14] ,
$(a_1, a_2, \cdots, a_T)$。
(3) LSTM ,
; $(a_1, a_2, \cdots, a_T)$
LSTM $(\boldsymbol{h}_t, \boldsymbol{c}_t) = \mathrm{LSTM}(a_t, h_{t-1}, c_{t-1})$, $t$

$\boldsymbol{h}_t$ $\boldsymbol{c}_t$, LSTM
128 。
(4) $\boldsymbol{h}_t$ $\mathrm{SOFTMAX}(h_j) = \dfrac{\exp(h_j)}{\sum_{i=1}^{C} \exp(h_i)}$
, $j$
, $j$。




3 CLSTM
Fig. 3 CLSTM method for gait pattern classification

## 3

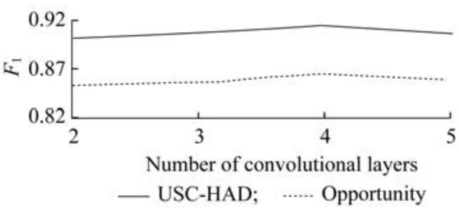
### 3.1 实验数据

Southern California University
USC-HAD[4] 。USC-HAD 14
, 11
, 1。 100 Hz,
$N$ 100。

### 3.2 实验结果与分析

#### 3.2.1 模型参数对分类的影响

CLSTM 4 2。




4 $F1$
Fig 4 Trend of the effect of number of convolution layers on $F1$

4 , 4 ,
(USC-HAD opportunity[15])
, 4
, ,
, 。
2 , 2 36×
$N$ $\boldsymbol{Y}$, $F1$
$\boldsymbol{Z}$( (1)) 7%;
, 5×5。

, 5×5
CNN
, ,
。

表 1
Table 1 Gaits pattern

| No. | Activity | Description |
|---|---|---|
| 1 | Walking forward | Subject walks forward in a straight line |
| 2 | Walking left | Subject walks counter-clockwise in a full circle |
| 3 | Walking right | Subject walks clockwise in a full circle |
| 4 | Walking upstairs | Subject goes up multiple flights |
| 5 | Walking downstairs | Subject goes down multiple flights |
| 6 | Running forward | Subject runs forward in a straight line |
| 7 | Jumping | Subject stays at the same position and continuously jumps up and down |
| 8 | Sitting | Subject sits on a chair either working or resting. Fidgeting is also considered to belong to this class |
| 9 | Standing | Subject stands and talks to someone |
| 10 | Elevator up | Subject rides in an ascending elevator |
| 11 | Elevator down | Subject rides in a descending elevator |

表 2 $F1$
Table 2 Effect of size of input data and convolution kernel on $F1$

| | Accelerometer | $Z$ | $Y$ |
|---|---|---|---|
| Channels | 3 | 9 | 36 |
| Filter size | 2×2 | 3×3 | 5×5 |
| $F1$ | 0.615 | 0.803 | 0.876 |

3.2.2 与传统方法的比较 CLSTM SVM[1]、HMM[7]、CNN[3] USC-HAD , 3 。 ,Subject 1、Subject 5、Subject 10 3 , Accuracy [12] 。 10 , 100 。

表 3

Table 3 Results comparison of the gait pattern classification methods

| Method | Accuracy/% | | |
|---|---|---|---|
| | Subject 1 | Subject 5 | Subject 10 |
| SVM | 75.6 | 82.6 | 80.1 |
| HMM | 73.5 | 80.3 | 81.3 |
| CNN | 81.7 | 83.0 | 83.7 |
| CLSTM | 87.6 | 87.1 | 86.6 |

3 ,CLSTM , ;CLSTM CNN SVM HMM , CNN , 。

CLSTM Subject 1、Subject 5、Subject 10 CNN 3% , LSTM , , , 。

3.2.3 对 5 种和 11 种步态模式数据分类的实验结果与分析 , " "、" " " ", , 5 ( 、 、 、 ) 11 ( 1) , 4、 5 。

表 4 5

Table 4 Results comparison of classifying 5 gaits pattern

| Method | Accuracy/% | | |
|---|---|---|---|
| | Subject 1 | Subject 5 | Subject 10 |
| SVM | 73.2 | 73.6 | 74.2 |
| HMM | 76.1 | 75.9 | 75.5 |
| CNN | 79.8 | 80.3 | 80.7 |
| CLSTM | 82.3 | 83.1 | 82.3 |

4、5 , 5 11 ,CLSTM SVM、HMM、CNN 。SVM HMM 11 5 , CNN CLSTM , , 。CLSTM CNN 5%, LSTM 。

表 5 11

Table 5 Results comparison of classifying 11 gaits pattern

| Method | Accuracy/% | | |
|---|---|---|---|
| | Subject 1 | Subject 5 | Subject 10 |
| SVM | 75.6 | 82.6 | 80.1 |
| HMM | 73.5 | 80.3 | 81.3 |
| CNN | 81.7 | 83.0 | 83.7 |
| CLSTM | 87.6 | 87.1 | 86.6 |

3.2.4 CLSTM 方法对 11 种步态模式的分类实验

, USC-HAD 300 , CLSTM CNN 11 , CNN , 6。 6 ,CLSTM CNN 3%~10%, , LSTM ; " "," " " "3 ,CLSTM CNN 7% , , LSTM 。

## 4

CLSTM ,CNN , LSTM 。

。 (1 s), , , , 。 。

表 6 CNN CLSTM 11

Table 6 Results comparison of CNN and CLSTM in classifying 11 gaits pattern

| Gait pattern | CNN | | CLSTM | | Increase rate/% |
|---|---|---|---|---|---|
| | Gait numbers | F1/% | Gait numbers | F1/% | |
| Walking forward | 201 | 67 | 222 | 74 | 7 |
| Walking left | 210 | 70 | 233 | 77 | 7 |
| Walking right | 193 | 64.3 | 218 | 72.7 | 8.4 |
| Walking upstairs | 232 | 77 | 260 | 86.7 | 9.7 |
| Walking downstairs | 226 | 75 | 256 | 85 | 10 |
| Running forward | 253 | 84 | 266 | 88 | 4 |
| Jumping | 278 | 92 | 286 | 95 | 3 |
| Sitting | 288 | 96 | 288 | 96 | 0 |
| Standing | 277 | 92.3 | 283 | 94 | 1.7 |
| Elevator up | 262 | 87.3 | 273 | 91 | 3.7 |
| Elevator down | 259 | 86.3 | 274 | 91 | 4.7 |

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