周工作报告

基于穿戴式传感器的动作识别

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内容概要

- 动作识别简介
- WSAR系统结构
- 特征提取
- 学习算法
- 评估矩阵

1.1 动作识别系统分类

Table 1: Analysis of VSAR, WSAR, and OUAR

Categories	Strength	Limitation	Applications
VSAR	1) Video includes richest information; therefore, its applied range is most widely 2) Environmental setting up is easy	1) Violating privacy 2) Sensitive to environment (e.g. light condition and viewpoint variation)	1) Healthcare 2) Security 3) Interactive applications 4) Content based video analysis
PSAR			
WSAR	1) Environmental setting up is not required 2) Good for the applications which require explicit motion analysis	1) Wearing sensors is a burden 2) Unable to separate similar actions (e.g. making tea and coffee)	1) Healthcare 2) Interactive applications
OUAR	1) Do not violate privacy 2) Good at recognize goal-oriented activities	1) Recognizable activities need to be related with objects 2) Environmental setting up needs more effort than VSAR and WSAR	1) Healthcare 2) Security

动作识别分为两大类：基于视频传感器的动作识别以及基于物理传感器的动作识别。基于物理传感器的动作识别又分为基于穿戴式传感器的动作识别以及基于外部传感器的动作识别。

1.2 动作分类

TABLE I
TYPES OF ACTIVITIES RECOGNIZED BY STATE-OF-THE-ART HAR SYSTEMS.

Group	Activities
Ambulation	Walking, running, sitting, standing still, lying, climbing stairs, descending stairs, riding escalator, and riding elevator.
Transportation	Riding a bus, cycling, and driving.
Phone usage	Text messaging, making a call.
Daily activities	Eating, drinking, working at the PC, watching TV, reading, brushing teeth, stretching, scrubbing, and vacuuming.
Exercise/fitness	Rowing, lifting weights, spinning, Nordic walking, and doing push ups.
Military	Crawling, kneeling, situation assessment, and opening a door.
Upper body	Chewing, speaking, swallowing, sighing, and moving the head.

同样的算法对不同类别的动作起到的效果不一样，因此再设计系统时要考虑到动作的分类。

1.3 动作识别的数学定义

定义： 集合W={W0, ..., Wm−1}是m个大小相等的时间窗口，每个窗口都被部分或者全部标记, 每个Wi 包含了一个时间序列 Si = {Si,0, ..., Si,k−1}，集合中的每个元素都来自k 个待测量的属性。集合A={a0, ..., an−1}是表示动作的标签，动作识别的目的就是找到一个映射函数f: Si →A，它可以评估Si中所有可能的值，因此f(Si)就是时间窗口Wi说表示的动作的一个最接近的值。

1.4 例子

A time window in the raw training dataset

Acceleration signals

w	t	a_x	a_y	a_z	Activity
j	0	1.3	-2.1	0	Running
j	$1/s_1$	1.4	-2.3	0.1	Running
j	$2/s_1$	1.1	-2.6	0	Running
...	...	...	...	...	...
j	t_{max}	1.8	2.2	-0.4	Running

Physiological signals

w	t	HR	...	RR	Activity
j	0	120	...	15	Running
j	$1/s_2$	120	...	16	Running
j	$2/s_2$	120	...	15	Running
...	...	...	...	...	...
j	t_{max}	121	...	18	Running

Environmental signals

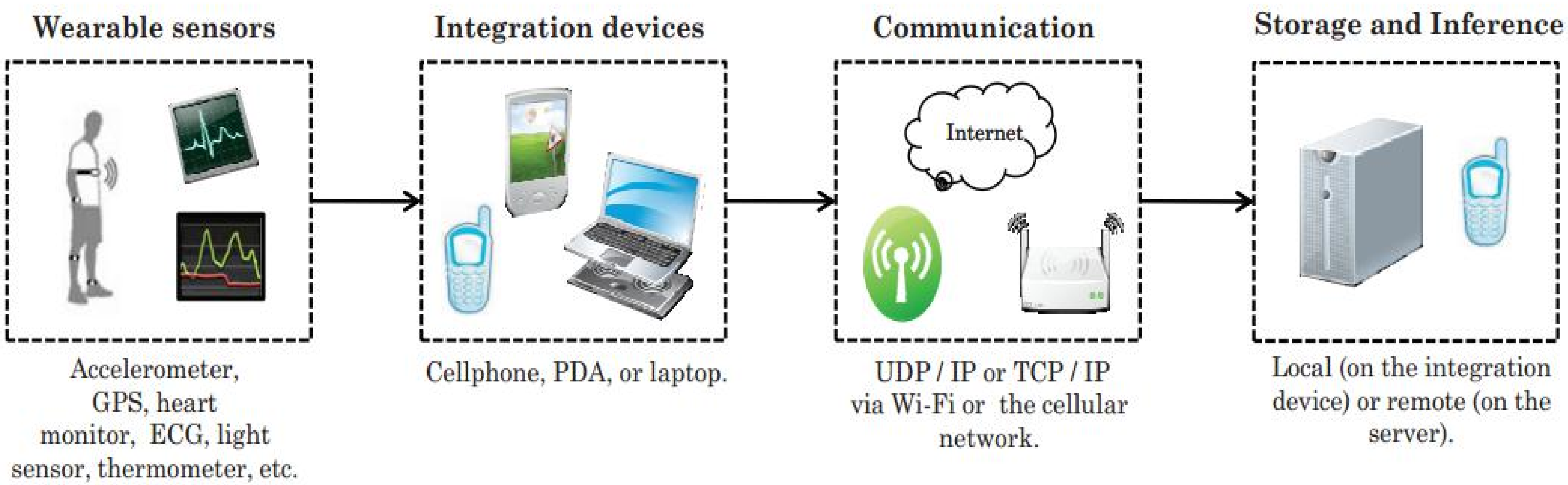
w	t	Temp	...	Hum	Activity
j	0	120	...	15	Running
j	$1/s_3$	120	...	16	Running
j	$2/s_3$	120	...	15	Running
...	...	...	...	...	...
j	t_{max}	121	...	18	Running

Processed training dataset

w	f_0	...	f_n	Activity
0	231	...	-6.2	Unknown
...	...	...	...	...
j	543	...	8	Running
...	...	...	...	...
k-1	339	...	7.1	Upstairs

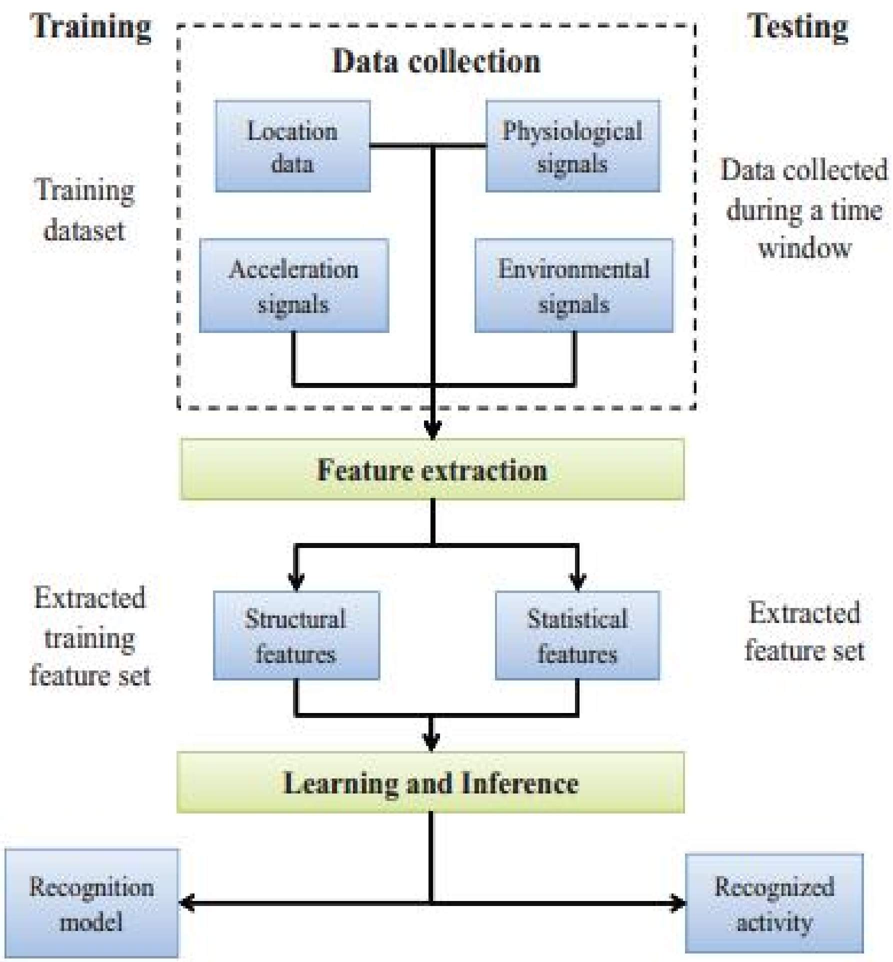
过渡窗口内可能同时出现两个动作，但是当过渡窗口的数量远远小于时间窗口的数量时，这种误差是可以忽略的。

2.1 系统结构



系统设计要考虑的因素 (1)属性选取(2)obtrusiveness(3)数据收集协议(4)系统性能(5)能耗(6)processing(7)灵活性

2.2 工作过程



Training
Data collection
Testing
Location data
Physiological signals
Training dataset
Data collected during a time window
Acceleration signals
Environmental signals
Feature extraction
Extracted training feature set
Structural features
Statistical features
Extracted feature set
Learning and Inference
Recognition model
Recognized activity

3. 特征提取

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \qquad (1)$$

$$RMS(Y) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {y_i}^2} \qquad (2)$$

$$\sigma_y = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (y_i - \bar{y})^2} \qquad (3)$$

$$\sigma_y^2 = \frac{1}{n-1}\sum_{i=1}^{n} (y_i - \bar{y})^2 \qquad (4)$$

$$MAD(Y) = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} |y_i - \bar{y}|} \qquad (5)$$

$$Energy(Y) = \frac{\sum_{i=1}^{n} {F_i}^2}{n} \qquad (6)$$

特征提取的方法分为两类：统计学方法和结构法

3. 特征提取

特征提取的方法分为两类：统计学方法和结构法

给定时间序列Y(t),，构建函数 f(Y(t)) =ˆ Y(t)，其中ˆ Y(t)近似代表Y(t) ，通过计算平方误差(SSE)评估ˆ Y(t)是否对 Y(t)进行了很好的拟合，SSE计算公式如下：

$$SSE = \sum_{t} \left(Y(t) - \hat{Y}(t) \right)^{2} \tag{7}$$

要提取的特征就是表示ˆ Y(t)的参数

4. 学习算法

Type	Classifiers
Decision tree	C4.5 and ID3
Bayesian	Naïve Bayes and Bayesian Networks
Instance Based	k-nearest neighbors
Neural Networks	Multilayer Perceptron
Domain transform	Support Vector Machines
Fuzzy Logic	Fuzzy Basis Function and Fuzzy Inference System
Regression methods	MLR, ALR
Markov models	Hidden Markov Models and Conditional Random Fields
Classifier ensembles	Boosting and Bagging

5. 评估矩阵

对n个类进行分类的结果可以用混淆举证Mn×n表示。Mij表示来自类i的实例被划分到类j的数量.。在只有两个类的时候可以做如下定义：

True Positives(TP): positive 实例被划分为positive类的数量。

True Negatives(TN): negative实例被划分为negati-ve类的数量。

False Positives(FP): negative实例被划分为positive类的数量。

False Negatives(FN): positive实例被划分为negati-ve类的数量。

5. 评估矩阵

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

$$F - measure = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{11}$$

谢谢大家！

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