Reading summary

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6/17/2020

Smartphone-Based Recognition of States and State Changes in Bipolar Disorder Patients

Study Overview and Data Acquisition

Objective

Introduce a system based on smartphone-sensing, which is able to recognize depressive and manic states and detect state changes of patients suffering from bipolar disorder.

Real-life Dataset

- 10 patients
- 10 month, 12 weeks per patient (in total over 800 days of data tracing 17 state changes) at a rural area psychiatric hospital in Austria
- recorded by four different sensing modalities

Data Collection

1. A developed logging application in **Android smartphone** was designed to record all sensor data automatically.

2. The selection of patients was entirely done by the ward's psychiatrists' perception.

3. Psychological state examinations (HAMD or YMRS) were frequently performed every three weeks:

Seven Classes

-3 for severe depression; +3 for severe mania with intermediate steps of depression; slight depression; normal (0); slight mania and mania

Recognizing the State

Sensors and Features

- Social interaction: phone + sound calls/text message.
- Physical motion
- Travel patterns: GPS/Acceleration

Classification Method

- Training: For the actual classification, features were first transformed using a Linear Discriminant Analysis. The classes for the classification were defined according to the diagnosis provided by psychologists.
- Test: The Naive Bayes classifier included in Weka, k-nearest neighbor, j48 search tree and conjunctive rule learner. Similar results.
- repeat 500 times in a cross-validation approach

Recognizing the State

TABLE I
ACCURACY IN % (# OF TOTAL INSTANCES) AND RECALL PRECISION
FOR PHONE, SOUND, AND SENSOR-FUSION (CLASSES/STATES:
SEE SECTION II-B)

Patients	PHONE	Rec/Prec	SOUND	Rec/Prec	Fusion	Rec/Prec
p0102	75(46)	64.4/70.1	66(46)	51.2/40.4	73(46)	58.5/68.0
p0201	62(38)	52.5/53.2	68(32)	60.8/62.0	71(38)	58.7/66.4
p0302	71(60)	62.0/63.6	74(60)	64.5/52.0	71(60)	60.7/65.3
p0602	36(35)	33.9/35.0	76(35)	68.5/78.7	65(35)	57.0/48.0
p0902	68(41)	63.7/65.3	71(41)	68.5/68.5	68(41)	62.3/65.5
p1002	65(37)	78.7/69.4	65(37)	54.0/40.8	65(40)	53.3/41.4
Average	**66%**	**61/58**	**70%**	**60/59**	**69%**	**52/55**

TABLE II
COMPARISON OF RECOGNITION OF DIFFERENT MODALITIES AND FUSION OF
DIFFERENT MODALITIES AND OF ALL-IN FUSION

(av. # instances)	Recall (std)	Precision (std)	total (std)
PHONE (43)	54.4% (11.4)	37.3% (29)	64.2% (13)
SOUND (43)	61.3% (7.3)	24.2% (31)	69.8% (4.5)
FUSION P + S (43)	**58.4%** (3.2)	**59.0%** (11.3)	**69.3%** (3.5)
ACC (48)	62.9% (7.9)	64.8% (7.8)	71.7% (3.8)
LOC (33)	72.3% (14.5)	76.5% (13.7)	81.7% (6,5)
FUSION A + L (49)	**66.3%** (11.0)	**57.9%** (16.6)	**75.6%** (6.2)
all-in FUSION (49)	**65.8%** (8.8)	**72.0%** (12.2)	**76.4%** (4.1)

The recognition accuracies is 76% by fusing all sensor modalities. This means that, as assumed earlier, the combination of social behavior, travel patterns, and movement, by covering different aspects in the patient's behavior, optimizes the state detection and provides better results than single sensors or fusion of only a few sensor modalities

Detection of State Changes

1. Build a model of a single "default state".

2. All points falling outside this model are classified as a "change."
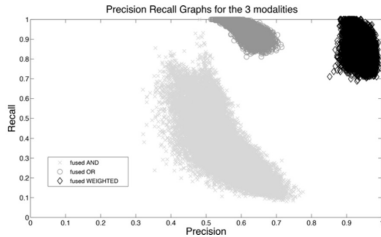

Fig. 1. Precision/recall graph of the three concatenation modalities of the state change detection fusion using different thresholds.

TABLE III
STATE CHANGE DET. RESULTS OF THE DIFF. FUSION MODALITIES

	Recall	Precision
A+L weighted Fusion	**96.40%**	**94.50%**
All-in AND Fusion	42.87%	61.18%
All-in OR Fusion	92.15%	70.28%
All-in WEIGHTED Fusion	**97.36%**	**97.19%**

The state change detection precision and recall is over 97%.

Multivariate Hidden Markov Models for Personal Smartphone Sensor Data: Time Series Analysis

Objective

Smartphone-based human activity recognition (HAR) offers growing value for health research. Assess the general potential for Hidden Markov Models (HMMs) to be used in modelling a person's physical status by means of multivariate smartphone sensor data.

Data

Ground-truth data from a small self-report study.

11 sensors: accelerometer, gyroscope, Wi-Fi, location (pseudo-sensor consisting of GPS and network-based location data), battery level, humidity, pressure, temperature, light, proximity, orientation (pseudo-sensor based on accelerometer, magnetometer), and Bluetooth.
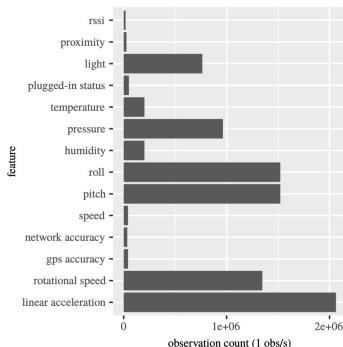
14 features:

Fig. 1. Observation counts per feature.

Model

▶ Assumption:

1. HMM state-specific dwell times (number of contiguous time-steps in a particular state before transitioning) follow a geometric distribution.
2. Any two observations are conditionally independent, given that they are drawn from the same state.

▶ Training:

1. Parameters: transition probability matrix, the unconditional (starting) state probability vector, and those associated with the state-conditional probability distributions.
2. Using supervised Maximum a posteriori (MAP) estimate, a predicted state sequence will be produced by the Viterbi algorithm.

▶ Validation:

Using Four-fold cross-validation with macro F1score statistic. Comparing the output sequence of states to the actual sequence of states, and producing a confusion matrix.

Model

▶ Selection:

Experimented with a variety of state-conditional probability distributions.

Parametric

The chief option studied was a lognormal fit to each of the magnitudes of linear acceleration and rotational velocity.

Non-parametric

1. a univariate kernel density estimate (KDE)
2. a naive multivariate extension of the first

Key	Feature
RS	3D rotational speed
LA	Magnitude of 3D linear acceleration
All	All collected features
	State-conditional Probability Distribution
E	Univariate empirical
L	Lognormal
ML	Log-transformed multivariate normal
ME	Naïve multivariate empirical
	State Configuration
OP	Off-/on-person
OSSW	Off-person/sitting/standing/walking
OV	Off-/on-vehicle
IO	Indoors/outdoors

Results

TABLE VI.   HMM LOGNORMAL RESULTS, AVERAGED.

Participant ID		State configuration			
		OP	OSSW	OV	IO
	1	0.85	0.73	0.61	NA
	2	0.63	NA	0.53	0.52
	3	0.44	0.22	0.49	0.51
	4	0.63	NA	0.62	0.52
	5	0.79	0.50	0.68	0.63
	6	0.51	0.41	0.78	0.33
	7	0.90	0.56	0.60	0.85
	8	0.55	0.42	0.56	0.63
	9	0.78	0.51	0.58	0.74
	10	0.65	0.30	0.63	0.46

TABLE VII.   NAÏVE BAYES LOGNORMAL RESULTS, AVERAGED.

Participant ID		State configuration			
		OP	OSSW	OV	IO
	1	0.80	0.57	0.49	1.00
	2	0.35	0.21	0.49	0.48
	3	0.66	0.36	0.58	0.49
	4	0.43	0.29	0.40	0.56
	5	0.72	0.39	0.54	0.56
	6	0.49	0.11	0.56	0.65
	7	0.81	0.55	0.57	0.76
	8	0.65	0.44	0.50	0.59
	9	0.72	0.48	0.57	0.70
	10	0.61	0.34	0.52	0.44

The HMMs achieved reasonable accuracy in classifying phone off-person vs. phone on-person, off-vehicle vs. on-vehicle, and phone off-person vs. sitting vs. standing vs. walking, for some participants.

Tables VI and VII show the comparison between a Gaussian NB classifier and a Gaussian HMM. They each display the averaged results of univariate Gaussian fits to linear-acceleration and rotational-speed, across all participants and state configurations.