Prediction of Psychiatric Mental States for Emergency Telepsychiatry

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Abstract
Monitoring rapid behavior change of emergency psychiatric patients’ is one of the key challenges in emergency psychiatry. This paper proposes an emergency telepsychiatry system with Maximum Entropy Markov model (MEMM) based emergency psychiatric state recognition skill. In this system, patients’ real-time vital psychosomatic diseases symptoms are collected through body sensor network (BSN) and then analyzed the collected data with patients’ historical data of diseases, habits, family, genetics and rehabilitations in IaaS healthcare cloud. The emergency psychiatric states of patients’ are modeled as the discrete set of states of Maximum Entropy Markov model (MEMM), where sensor observations and patients’ history are considered as the observations of MEMM. The Viterbi, a machine learning algorithm is used to generate the most probable psychiatric mental state sequence based upon those observations; and prognosis of emergency psychiatric state is mined through proposed ensemble prediction algorithm.

1. Introduction
Psychiatric emergency covers broader range of mental illness like suicide efforts, drug intoxication, alcohol intoxication, homicide and violent behaviors etc. but in this research we consider only the suicide and homicide-suicide emergency psychiatric crisis. The suicide deaths are listed in top 10 leading causes of deaths in USA. The suicide rate of Republic of Korea is highest among 30 OECD countries and it is about 33.50 deaths per 10,00,000 population in 2010 according to the OECD factbook 2013 [1]. The study of domestic and peer violence among adolescents in secondary school of Macedonia shows that effective telemedicine network is very useful tool for dealing with long-acting and crippling medical problems like family and peer violence [2]. Emergency telepsychiatry is a psychiatric care using telematics platform of individuals, who are experiencing potential imminent dangerousness to themselves (suicide) or dangerousness to others (homicide) [3].

We define psychiatric mental states objectively as normal, atypical and emergency. The subject with sound mental health is considered as normal, and the psychiatric patients are painstaking as atypical and emergency mental states. Patients’ suicidal ideation (i.e. emergency mental state) is assessed by the psychiatrist through question number 9 of Beck Depression Inventory-II (BDI-II) [4] as shown in figure 1 or using scale for suicide ideation (SSI).

2. System Description
The system architecture of the proposed psychiatric mental state prediction method for emergency telepsychiatry (PPMSET) is shown in figure 2. We indicate the data flow on the figure by leveling the flow sequence from 0 to 6. We assumed that patient’s personal, medical (e.g. psychiatric scales ratings), treatment and family histories are stored on private cloud of patient’s hospital. The non-invasive bio-sensor observations are collected through body sensor networks (BSN). All three channels of Electro-Dermal Activity (EDA) sensor, ElectrocardioGram (ECG) sensor, and Blood Volume Pulse (BVP) sensor are used to extract features, which are the representatives of psychiatric risk factors for emergency psychiatric mental state e.g. skin conductance level can demonstrate the stress level, R-R and QTc intervals can demonstrate depression level, the variation of peak to peak interval and pinch of the BVP can indicate the frustration level. Cloud service brokerage (CSB) received sensor observations
from sink node of BSN and then extracted features from the received signals. For example, the preprocessed and extracted features of EDA sensor is shown in Fig. 3. Then CSB sends data request to patient’s hospitals private cloud and sends extracted sensor features to healthcare cloud. The private cloud of hospital dispatch necessary patient’s information to healthcare cloud. The healthcare cloud has the developed mental state sequence generator (MSSG) based on Maximum Entropy Markov model (MEMM)[5] mental state model. The MSSG uses Viterbi algorithm [6] to generate mental state sequence from patients all form of observations or features. Then the proposed ensemble algorithm predicts the emergency mental state from generated mental state sequence. However, MSSG is trained in prior through collected dataset [7].

3. System Modeling and Algorithm Design
In MEMM, we consider total M states in the recommended maximum entropy Markov process as shown in figure 4, and the set of states is $S = \{s_1, s_2, \cdots, s_M\} = \{\text{normal, atypical, emergency}\}$. The observations are taken from patients’ body sensor networks observations with psychiatric screening scores, patients’ medical history, traits and family history etc. We consider the observations set as $O = \{o_1, o_2, \cdots, o_N\}$, where $N$ is the number of total observations. Our primary goal is to find out a state sequence $Q = \{q_1, q_2, \cdots, q_p\}$ of $S$ based on the current observations at a given time $t$. Unlike HMM, which requires transition $P(s_i|s_{i-1})$, emission $P(o_i|s_i)$ and initial $P(s_i)$ probabilities, the MEMM requires a single function $P(s_i|s_{i-1}, o_i)$ that can be easily obtainable from an exponential model (1), where $f_k$ is the feature values and $w_k$ is the trainable weights of multinomial logistic regression.

$$P(s_i|s_{i-1}, o_i) = \frac{\exp(f_k \cdot w_k)}{\sum_{t \in S} \exp(f_k \cdot w_k)}$$

We assume that the weights are distributed using normal distribution $\mathcal{N}(0, \sigma)$. Using the Gaussian prior we can find the smaller weight by subtracting square of weights as (2).

$$\hat{w} = \arg \max_w \sum_{t \in S} \log P(s_i|o_i) - \sum_{k=1}^{N} \frac{w_k^2}{2 \sigma^2}$$

By performing the training we obtain the weights $w$ to find out $P(s_i|s_{i-1}, o_i)$ for (1). Finally, Viterbi returns psychiatric mental state sequence $Q = \{q_1, q_2, \cdots, q_p\}$ according to the observations $o_i$.

To predict the psychiatric mental state we compare the generated state sequence result with weighted preference approval voting results and define the ensemble result as the predicted psychiatric mental state. The proposed algorithm is as follows:

**Algorithm 1: Ensemble Prediction Mental State (MaxEnt, O)**

1. $Q$=Viterbi (MaxEnt, O), where $Q = \{q_1, q_2, \cdots, q_p\}$ is the sequence of state generated MSSG of healthcare cloud.
2. Count the frequency of each of the individual state $s_1$, $s_2$, $s_3$, ... , $s_M$ of generated state sequence Q.
3. Determine the state having maximum cardinality $s_{mc} = \arg \max_{s \in S} |s_1|$
4. Determine plausible psychiatric states (or candidates) $v_k = \{c_1, c_2, \cdots, c_M\}$ of each $o_i \in O$ according to approval voting scheme, where $O = \{o_1, o_2, \cdots, o_N\}$ is the observation set.
5. Group the $o_i$’s with similar vector $v_k$ and determine the
weighted cardinality $w_{c_jk} = \sum_{q \in \mathbb{N}} w_{ij}$ of each of the states $c_j$ of $v_k$ totaling the weight $w_{i}$ of each group.

6. For each $c_j$ the element of candidate set $C = \{c_1, c_2, \ldots, c_M\}$.

7. Compare head to head total cardinalities among the candidates’ $c_i$ (i.e. psychiatric mental states) and extract the candidate which has highest total head to head weighted cardinality (i.e. the PAV winner) $s_{w_{PAV}} = \arg\max_{c_j} \{ w_{c_jk} \}$

8. Determine $s_{mc} = \arg\max_{s_j} \{ |s_j| \}$

9. Determine $s_{w_{PAV}} = \arg\max_{c_j} \{ w_{c_jk} \}$

10. Calculate $M_{mc} = \frac{|s_{mc}|-|s_{mc'}|}{\max (|s_{mc'}|, |s_{mc}|)}$

11. Calculate $M_{w_{PAV}} = \frac{|s_{w_{PAV}}|-|s_{w_{PAV'}}|}{\max (|s_{w_{PAV'}}, |s_{w_{PAV}}|)}$

12. For each $s_i$ the element of set $S$ i.e. $\{s_1, s_2, \ldots, s_M\}$

13. Determine the number of instances of $s_i$ in conjectured psychiatric mental state set $\{s_{fa}, s_{sw}, s_{smc}\}$

14. Set $\hat{s} = s_i$, where $s_i$ has the maximum number of instances in $\{s_{fa}, s_{sw}, s_{smc}\}$

15. End for

16. End for

17. return $\hat{s}$

4. Performance Evaluation

We evaluate the performance of the proposed PPMSET system, by studying prediction accuracy. We divide our total data set into three parts. We use 1/3 of total data set for training purpose, 1/3 for cross validation set and 1/3 for testing purpose. In our data set, we consider total 36 features and 30 subjects. Figure 5 and table 1 represents the performance of the proposed prediction approach and we observed average 84.33% accuracy.

5. Conclusion

The proposed telepsychiatry system may use in mental hospitals, clinics, and rehabilitation centers as an expert system and as the complementary model of legacy mental healthcare system. The performance of the system is yet to be clinically investigated, though the observed psychiatric state prediction accuracy is 84.33% in empirical laboratory setup with a dataset of 30 subjects.

Table 1: The confusion matrix shows the performance of proposed prediction algorithm

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