Cloud Based Mental State Monitoring System for Suicide Risk Reconnaissance Using Wearable Bio-sensors

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ABSTRACT
Development of wireless body- and bio-sensor network opens a new horizon of healthcare especially to measure the vital physical signs of personnel for disease diagnosis and patient monitoring. And the cloud computing technology has enabled patient monitoring service dynamically scalable and ubiquitously accessible. The success of suicide risk reconnaissance is depends on effective prediction of mental states. This paper proposes a suicide risk scouting prototype by predicting mental states in cloud environment. In this system, patients’ real-time vital diseases symptoms are collected through wireless body area network (WBAN) and then analyzed the collected data in healthcare cloud platform with patient’s historical repository of diseases, habits, rehabilitations and genetics. Here, the mental statuses of patients have been modeled as the discrete set of states of hidden Markov model (HMM), where WBANs annotations and stored facts of patients in cloud are considered as the observations of HMM. Subsequently, the Viterbi, a machine learning algorithm has been applied to generate the most probable mental state sequence to monitor suicide risk of mentally disordered patients. Finally, the proposed system is validated by deploying this model on mental patients dataset.

Categories and Subject Descriptors
C.2.4 [Computer-Communication Networks]: Distributed Systems – Distributed Applications

General Terms
Human Factors

Keywords
Mental State Monitoring, Hidden Markov Model, Cloud Computing, Suicide, Mental Health

1. INTRODUCTION
According to the definition of Diagnostic and Statistical Manual of Mental Disorders (DSM-IV), the mental disorders is conceptualized as a clinically significant behavioral or psychological syndrome or pattern that occurs in an individual and that is associated with present distress or disability or with a significantly increased risk of suffering death, pain, disability, or an important loss of freedom [1]. Conversely, mental health is the nonexistence of mental disorder. Mental health monitoring is more challenging than the physical health monitoring because human mentality varies dynamically and it is difficult to fetch the patterns from the mental behavior. Also, mental behavior differs over so many metrics like age, ethnicity, education, marital status, family history and habits etc. However, human brain chemistry changes over different mental disorders but still causes and effects are not fully explored. And pinpointing the location of mental disorder in our brain is very difficult (almost impossible) as our brain consists of about 100 billion neurons and glial cells, and the neurons form the telecommunications network in the brain to communicate each other and also carry the signals back and forth between your brain and the rest of your body [2]. As a result, it is not possible to diagnose most of mental diseases like bipolar disorder using some definite pathological examination.

Mental state monitoring is necessary to diagnose different mental disorders, like to identify the manic and depressive episodes of bipolar disorders. The motivation of this research is not to diagnose the mental diseases, rather in this research we want to monitor the mental states irrespective of mental disorders to explore suicidal temperament of mentally sick patients’.

The individuals of different mental disorders have atypical, suicidal and/or homicidal tendency [3][4]. As there is no clinical model exists for emergency homicidal psychiatry, thus the normal, atypical and suicidal mental states have been considered to model the proposed system.

A clinical model of suicidal behavior of psychiatric patients is described in reference [22], where suicidal ideation scale is used. To model normal, atypical and suicidal mental state, we also used the scale of suicide ideation (SSI) presented in reference [23]. The SSI positive means the patient is living with the risk of suicide. Any mental disordered patient with negative SSI score is considered as the patients’ having atypical mental state.

2. RELATED WORKS
The stress, depression and anxiety are the most influential features of atypical, homicidal and suicidal mentality. In this section, we reviewed some articles regarding depression, stress and anxiety measurement through some wireless sensors. Mental state monitoring was always a challenging job for the researchers of neuroimaging. In 2006, John-Dylan Haynes & Geraint Rees published their research in Nature Reviews Neuroscience, where they revealed the possibility to decode human’s mental state such as conscious experience and covert attitude by assessing non-invasive measurement of brain activity [5].
In our proposed system, we used Electroencephalography (EEG) sensors neuroimaging observations to monitor brain and sleep disorders of mentally sick patients, like patients with severe depression. A Distributed wireless intelligent sensor based stress monitoring system is proposed in reference [6]. In that paper, author’s collected EEG and Electrocardiography (ECG) sensors through body area networks (BAN), then measure the heart rate variability (HRV) to quantify patients stress level.

The authors of reference [7] proposed an ambulatory stress monitoring system through BAN of Electromyography (EMG), Electro Dermal Activity (EDA) and respiratory inductive plethysmography (RIP) sensors. They also develop a heart rate monitoring (HRM) strap to observe the HRV of patients.

The method of discrimination of stress from cognitive load is proposed by the authors of reference [8], where they used EDA sensors to measure skin conductance response (SCR) to classify stress from cognitive load. In our proposed system, we also used EDA sensors skin conductance level (SCL) observations to trace the stress level of patients. A mobile social interaction stress monitoring system is developed by the authors of reference [9]. In that works, the author used EDA, temperature and accelerometer sensor to recognize stress level of performing different cell phone activities.

MONitoring, treatment and pRediCtion of bipolar disorder episodes (MONARCA) is an European project, which opens the door of self-management, assessment and treatment of mentally sick bipolar patients using some tiny sensors [10]. MONARCA wearable system is presented in reference [11]. The wearable system consists of smart phone, wrist-worn sensors for monitoring patient’s activity and smart socks to recognize mental states of bipolar patients. The detail design and implementation of MONARCA system is presented in reference [12].

The MONARCA project is especially developed for monitoring the mental states of bipolar disorder patients, where they consider manic episode, mild depression episode and severe depression episode as the mental states of bipolar patient’s. In contrast, our proposal is for monitoring normal, atypical and suicidal mental states of mental disordered patients’ for assessing suicide risk.

3. SYSTEM DESCRIPTION

In the proposed cloud based mental state monitoring system for suicide risk reconnaissance (CBMSMS-SRR) has shown in figure 1. In the proposed system, WBAN is used for real life data accusation from patients with mental diseases. As the stress, depression, alcohol misuse and loss of consciousness are the major risk factors among all of the suicide risk carriers, the WBAN consists of three types of bio-sensors to measure stress, depression and alcohol consumption levels. Including the sink node the sensors are nine in number.

Electro-dermal activity (EDA) sensor is used to measure the stress level and emotional state [13], electroencephalography (EEG) sensor is used to measures pivotal brain disorders and sleep disorders, blood volume pulse (BVP) sensor is used to measure blood flow and heart rate variability to monitor emotional state, alcohol consumption and irritation level of the patient.

Patients’ personal, medical and genetic history like age, sex, ethnicity, marital status, living alone or not, history of any long term sickness, history of drug misuse, prevalence of alcohol misuse, history of predecessor’s violence, history of previous violence, history of hallucination, history of suicidal attempt and prevalence of mental illness etc. are stored in the public IaaS clouds. It is assumed that hospitals or rehabilitation centers have stored and updated patients’ medical and personal information on IaaS cloud frequently.

Cloud healthcare agents is responsible for collecting data from patients BANs and transfer it to the public clouds healthcare service providers compute as a service of IaaS cloud to generate the mental state sequence.

The compute as a service of IaaS cloud comprises a mental state sequence generator (MSSG), which is responsible for generating state sequence based on features supplied by cloud healthcare agent and the features extracted from IaaS cloud regarding patients medical and family history. MSSG is modeled through hidden Markov modeling and trained over Viterbi path counting algorithm. And MSSG generates maximum a posteriori mental state sequence using Viterbi algorithm.

Finally, the cloud healthcare service provider send back the generated mental state sequence to cloud healthcare agent. And cloud healthcare agent then send the current mental status of the patient to corresponding hospital, psychiatrist and sink node of the patients WBANs.

In the proposed system, each and every patient must have to register to the cloud healthcare agent to get the cloud based healthcare service. On the time of registration, patient is identified and authenticated with his social security number and international mobile subscriber identity (IMSI) of WBANs sink node.
As Health Insurance Portability and Accountability Act of 1996 (HIPAA)-compliant data security is inevitable for electronic and mobile healthcare services [20] [21]. The proposed system ensures authentication and privacy through patient’s social security number, PIN number and international mobile subscriber identity (IMSI) of sink node. Sensor observations are encrypted using 128-bit advanced encryption standard (AES) algorithm for transmission. The sink node or smart phone doesn’t store sensor observations or patient medical information. The IaaS cloud has secure platform for data processing and also has secure web server with transport layer security (TLS) and secure socket layer (SSL) for data communication through internet. To ensure data integrity cloud maintains strong encryption mechanism like AES, it has PKI infrastructure for privacy concern and data anonymization techniques for confidentiality.

The information flow of the proposed system architecture is also depicted in figure 1. The flow of sensor observations is represented by black arrows from sink node of WBAN to MSSG of cloud healthcare service provider via cloud healthcare agent. The flow of generated mental state sequence is directed by blue arrows from cloud healthcare service provider through cloud healthcare agent to patients’ healthcare staffs’ i.e psychiatrist, hospital, rehabilitation center, cell phone of patients and relatives etc. The flow of patients’ medical and family history is represented by magenta arrows from patients’ treatment center to IaaS cloud of healthcare service provider.

4. SYSTEM MODELING

Mental state monitoring is the vital part of suicidal risk reconnaissance. The triumph of suicide risk scouting persistently depends upon accurate and just-in-time determination of emergency mental states. As far we know, there is no such pathological diagnosis exists, which pinpoints the atypical and life-threatening mental states. Therefore, statistical and probabilistic measurement is the alternative way to model deadly mental states.

4.1 Probabilistic mental state modeling

To design and develop CBMSMS-SRR, we consider mental states as hidden, because these states are not fully or partially observable, but we can predict the states through some sensor observations and individuals medical & genetic history. As human mental states follow memoryless property that is prediction of future state based exclusively on current state. Thus, ergodic Hidden Markov Model (EHMM) is barely apposite to model mental states of individuals. We consider total M states in the recommended discrete time Markov process, and the set of states is $S=\{s_1, s_2, \ldots, s_M\}$, where all states are hidden.

The observations are partially taken from patients’ body sensor networks observations and partially taken from cloud i.e patients’ history and genetic data.

To model the system, we also consider the observations set as $O=\{o_1, o_2, \ldots, o_N\}$, where $N$ is the number of total observations. Our goal is to find out a state sequence $Q=q_1, q_2, \ldots, q_p$ of $S$ based on the perceived observations $V=v_1, v_2, \ldots, v_p$ at a given time $t$.

The defined HMM of mental states has three tuples, i.e Hidden Markov Model $\lambda=(\pi, T, E)$, where $\pi$ is set of initial states probabilities $\pi=\{\pi_i|\pi_i=P(q_0=s_i)\}$, state transition probabilities $T=t_{ij}=P(q=s_j\ | \ q'=s_i)$, where $q'$ is the previous state sequence, and emission probabilities $E=e_{ij}=P(v=o_j|q=s_i)$. The projected HMM is shown in figure 2, with defined parameters of transition and emission probabilities.

![Figure 2: Mental state model of CBMSMS-SRR](image)

4.2 Training procedure and validation

It is required to determine the tuples of HMM for deploying the foreseen mental state model in CBMSMS-SRR. The Baum-Welch algorithm is the popular one to determine the parameters like initial probability, transition probability and emission probability for HMM.

Algorithm 4.1 VPC Training ($\lambda_0, V$)

1. $\lambda_0=\lambda$; where $\lambda_0$ is the user specified initial model values
2. For $i=1$ to num iteration; where num iteration is the required number of iterations to converge.
3. $Q=\emptyset$; Where $Q$ is the queue to hold most likely state sequences.
4. For all training sequence on $V$; Where $V$ is the training data set.
5. $Q_{i} \leftarrow$ Calculate maximum joint probabilistic state sequence using Viterbi algorithm from $\lambda$.
6. Update $Q$ with $Q_{i}$
7. End for
8. $E_{ij} = $Expected number of occurrences in state $s_i$ at the starting time $t$
9. $T_{ij} = \frac{\text{Frequency of transitions from } s_i \text{ to state } s_j}{\text{Frequency of transitions from } s_i}$
10. $E_{ij} = \frac{\text{Frequency of being in state } j \text{ and observing symbol } v_i}{\text{Frequency of being in state } j}$
11. $\lambda \leftarrow \{E, T, \pi\}$
12. End for
In comparison of convergence time the lightweight Viterbi Path Counting (VPC) training algorithm [15] is efficient than Baum-Welch’s algorithm to determine the unknown parameters of HMM. The proposed mental state model is trained through VPC training algorithm using reference datasets [16] [17] [24-27]. The referenced datasets are not designed for the especial requirements of mental state monitoring, thus we prepare a revised dataset for the training, validation and testing purpose of mental state model for suicide risk scouting. The missing data of the revised dataset is prophesied by Expectation-Maximization (EM) algorithm.

The objective of mental state monitoring is to generate maximum a posteriori mental state sequence based on observations. The Viterbi algorithm is used to find out the most likely mental state sequence of patient’s to explore the existence of suicide risks.

### 4.3 Prognosis of suicide

In the proposed CBMSMS-SRR, the MSSG only generates mental state sequence based on observed variables. The prognosis of suicide has been determined from the generated mental state sequence for reconnaissance of suicide risk.

Let the generated state sequence is $Q = \{ q_1, q_2, \ldots , q_p \}$; As there are $N$ number of observations, the state sequence consists at least $N$ number of states, where each state might appear several times on the produced state sequence. To study the prognosis of suicide, the frequency of each of the state is counted and stored for analyzing the patient’s condition.

In the proposed mental state model, the state sets are considered as $S = \{ s_1, s_2, \ldots , s_M \}$, where $s_1=$Normal, $s_2=$Atypical, $s_3=$Suicidal. For readability, the normal, atypical and suicidal states are symbolized by $N$, $A$, $Su$ respectively.

Now, cardinality or frequency of $N$, $A$ and $Su$ i.e $|N|$, $|A|$ and $|Su|$ are determined from generated state sequence $Q$. Furthermore, $|X|$= max $\{|N|, |A|, |Su|\}$ is determined, where $X$ is the state having maximum cardinality. The value and cardinality of $X$ and cardinality of $Su$ are stored for prognosis analysis purpose i.e for comparison purpose with the future test results.

Considering $X$ as the result of future test, if $X$ is not $Su$ then patient is no longer lies on the high risk of suicide, but if $X$ is $Su$ and $|X|\neg\neg|X|$ then the patient’s condition moves towards the high risk of suicide.

Now, if the value of $|X|\neg\neg|X|$ then patients’ have good prognosis for recovery from suicide risk otherwise the patient remains in high suicide risk.

### 4.4 Mental state shifting pattern

The final objective of reconnaissance of suicide risk is finding out the mental state shifting pattern. The frequent mental state changing pattern is useful for treatment planning and medication of mental disordered patients.

Each and every test in CBMSMS-SRR generates the mental state sequence of incumbent patients. The patient may examine several times in a day or examine by following weekly and monthly schedule. In that case, the common mental state changing pattern can be determined from the generated state sequences.

Considering the simplest case of two state sequences $Q_i$ and $R_j$ of length $p$ and $u$ respectively:

$Q_i = \{ q_1, q_2, \ldots , q_p \} = \{ N, A, Su, Su, A, Su, A, Su, \ldots , A \}$

$R_j = \{ r_1, r_2, \ldots , r_u \} = \{ A, A, Su, Su, A, N, Su, A, \ldots , N \}$

A dynamic programming approach have been applied to find the longest common mental state subsequence $\{ A, Su, Su, A, Su, A, Su, A \}$ lies in both of the state sequence $Q_i$ and $R_j$. So, the determined frequent mental state pattern from the two consecutive test results comprises of atypical followed by suicidal states. To find out accurate mental state shifting pattern, we should consider multiple state sequences from multiple test results.

The dynamic programming approach recursively counts the sequential common states between two sequences and build a $p \times u$ table $T$ to store the counting frequency to generate maximum length common subsequence of mental states. Thus $T[i,j]$ stores the length of common sequential states in $Q_i$ and $R_j$; where $0 \leq i \leq p$ and $0 \leq j \leq q$. And the recursive formula (1) to generate table $T$ is as follows [18]:

$$T[i,j] = \begin{cases} 0 & \text{if } i = 0 \text{ or } j = 0 \\ T[i-1,j-1] + 1 & \text{if } i, j > 0 \text{ and } q_i = r_j \\ \max(T[i-1,j],T[i,j-1]) & \text{if } i, j > 0 \text{ and } q_i \neq r_j \end{cases}$$ (1)

When $T$ is generated, we can extract the longest common mental state subsequence $C$ using traceback method from index $[p,u]$ to index $[0,0]$ of $T$.

$$C = \{ c_1, c_2, \ldots , c_v \} = \{ A, Su, Su, A, Su, A \}$$

From $C$, we can observe the common mental state changing pattern of the mental disordered patients’.

In case of finding common mental state changing pattern from multiple state sequences, we can apply the fast multiple longest common subsequence algorithm to determine the maximum length common subsequence of mental states from the generated state sequences [19].

### 5. PERFORMANCE EVALUATION

To evaluate the performance of the proposed mental state model for suicide risk reconnaissance, we implemented the proposed system by configuring XenServer as the hypervisor for virtualization in private cloud and also develop an android application as an emulator to evaluate the performance of the proposed system shown in figure 3.

We measure three variables: true positives (TP) are the states those were correctly detected, false positives (FP) are the states those were falsely detected, and false negatives (FN) are the states those were missed to detect as positive. These variables are used to define two performance measurement scale; the precision (P) and the recall (R) using equation (2) and (3) respectively.

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$ (2)

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$ (3)

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 62 features from 201 subjects or patients. For evaluation purpose, we change
our sensor observations of five types of sensor and measure the precision and recall of our testing data.

Figure 3: a) Sensor observations in android emulator  b) Mental state sequence (partial) generated by MSSG.

Table-1 shows that using all sensors observation and historical information from cloud to measure mental states of any patient has highest precision and recall. From table 1, we also remarks that EDA sensor’s observation is most influential observation among the sensors because EDA observation changes the recall value 45.36 to 71.31, which proves the higher impact of stress and depression on suicide risk.

The precision and recall curves of figure 4, demonstrates that only the family and medical history is not sufficient in suicide risk reconnaissance. The area under the Test_mod 4 curve is 0.8234, which shows that the use of EDA, EEG and BVP sensors observation with patients’ history enhances the reconnaissance performance of suicide risk. Though the proposed model failed to address 100% of suicide perpetrators but it has reported the maximum portion of suicide cases.

<table>
<thead>
<tr>
<th>Testing Modalities</th>
<th>Used sensor observations and patients’ history</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test_mod 1</td>
<td>Without sensor observations (Only using patients’ medical, genetic and family history )</td>
<td>48.11</td>
<td>45.36</td>
</tr>
<tr>
<td>Test_mod 2</td>
<td>EDA sensor with patients’ history</td>
<td>74.02</td>
<td>71.31</td>
</tr>
<tr>
<td>Test_mod 3</td>
<td>EEG and EDA sensors with patients’ history</td>
<td>83.21</td>
<td>79.63</td>
</tr>
<tr>
<td>Test_mod 4</td>
<td>EEG, EDA and BVP sensors with patients’ history</td>
<td>86.37</td>
<td>82.23</td>
</tr>
</tbody>
</table>

Figure 4 Precision vs Recall curve of CBMSMS-SRR

In figure 5, we have shown our justification of using 62 features for CBMSMS_SRR. The figure shows that the error rate is gradually decreases with the increment of number of features for both test data and cross-validation data. And after 56 features the error rate is almost remain constant for both type of dataset. The curve of cross-validation data and test data is not smooth because of some influential observations, in which error rates are mostly depended.

6. CONCLUSIONS

Predicting mental states using some tiny sensors and cloud computing technology is a novel initiative to monitor patients of suicide risk and of some mental disorders. It supports to prevent some undesirable and unwanted live loosing. We hope early detection and monitoring of abnormal mental states can reduce the suicidal risk a significant amount. As EDA, EEG and BVP sensors are non-invasive bio-sensor, so we can easily setup and measure mental states of mental disordered patients or susceptible person through some minimal setup in home, medical center, clinic or hospital. Inadequacy of suitably structured and application oriented standard dataset of suicidal perpetrators of all nations is the key barrier of the prosperous employment of CBMSMS-SRR. The enhanced model may applicable to reconnaissance of homicide risk of mental disordered patients.
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7. REFERENCES