Computer Assisted Analysis System of Electroencephalogram for Diagnosing Epilepsy

Malik Anas Ahmad
Signal Image & Video Processing Lab,
EE, SBASSE, LUMS
Lahore, Pakistan
malik.anas@lums.edu.pk

Nadeem Ahmad Khan
Signal Image & Video Processing Lab,
EE, SBASSE, LUMS
Lahore, Pakistan
nkhan@lums.edu.pk

Waqas Majeed
Signal Image & Video Processing Lab,
EE, SBASSE, LUMS
Lahore, Pakistan
waqas.majeed@lums.edu.pk

***Abstract*—Automation of Electroencephalogram (EEG) analysis can significantly help the neurologist during the diagnosis of epilepsy. During last few years lot of work has been done in the field of computer assisted analysis to detect an epileptic activity in an EEG. Still there is a significant amount of need to make these computer assisted EEG analysis systems more convenient and informative for a neurologist. After briefly discussing some of the existing work we have suggested an approach which can make these systems more helpful, detailed and precise for the neurologist. In our proposed approach we have handled each epoch of each channel for each type of epileptic pattern exclusive to each other. In our approach feature extraction starts with an application of multilevel Discrete Wavelet Transform (DWT) on each 1 sec non-overlapping epochs. Then we apply Principal Component Analysis (PCA) to reduce the effect of redundant and noisy data. Afterwards we apply Support Vector Machine (SVM) to classify these epochs as Epileptic or not. In our system a user can mark any mistakes he encounters. The concept behind the inclusion of the retraining is that, if there is more than one example with same attributes but different labels, the classifier is going to get trained to the one with most population. These corrective marking will be saved as examples. On retraining the classifier will improve its classification, hence it will tries to adapt the user. In the end we have discussed the results we have acquired till now. Due to limitation in the available data we are only able to report the classification performance for generalised absence seizure. The reported accuracy is resulted on very versatile dataset of 21 patients from Punjab Institute of Mental Health (PIMH) and 21 patients from Children Hospital Boston (CHB) which have different number of channel and sampling frequency. This usage of the data proves the robustness of our algorithm.**

Keywords—Epilepsy, Electroencephalography (EEG), Machine Learning, Biomedical Signal Processing

I. INTRODUCTION

Epilepsy is a recurring neurological disorder, which is characterized by excessive neural activity yield in the brain. Almost 1% of the human population suffers from epilepsy [1] [2]. Detection and localization of abnormal, epilepsy-related brain activity is very important for diagnosing and curing of an epileptic disorder. Electroencephalogram (EEG) is a method for recording of electrical activity along the scalp. EEG signal represents fluctuations in the voltage caused by the flow of ionic current in the neurons. Epileptic seizures are accompanied by unique patterns in EEG, and therefore EEG is widely used to detect and locate the epileptic seizure and zone.

Duration of a typical diagnostic EEG recording varies from 40 minutes to few hours. However, prolonged EEG is opted if a seizure is not detected in shorter recordings. A prolonged EEG can last as long as 72 hours. A diagnostic procedure like this generates a huge amount of data to be manually inspected by the neurologist. This is could prove to be a daunting task for a neurologist.

Computer assisted analysis of an EEG supplements a neurologist in efficiently analysing the EEG data. It highlights the epileptic patterns in the EEG up to a significant level, thus reducing the data to be analysed and lessening the fatigue. These analysis software tools apply different signal processing and machine learning techniques on the EEG data to detect the epochs with epileptic patterns. This analysis also helps the neurologist in differentiating between the epileptic and non-epileptic but closely resembling artefact patterns. Along with classification these analysis software also provide simultaneous visualization of multiple channels which helps the clinician in differentiating between generalized and focal epilepsy. Currently available commercial computer assisted diagnosis tools for epilepsy are not user-friendly and they also don’t have a simple self improving mechanism. These software tools require the clinician to have a prior understanding of signal processing algorithms to exploit the full potential of the software. For this they hire technicians and rely on them. This makes that analysing procedure using that software tools prone to misinterpretation and over-interpretation as the manual marking get dependent on the expertise of the technicians [3] rather than the clinician himself [2] [4] [5] [6].

In the next section we will briefly describe the existing work in the field of computer aided EEG analysis for Epilepsy.

1051-4651/14 $31.00 © 2014 IEEE
DOI 10.1109/ICPR.2014.583

II. EXISTING WORK

EEG signals are non-stationary. Methods for analysing non-stationary signals, such as Discrete Wavelet Transform (DWT), Empirical Mode Decomposition (EMD) and time-frequency analysis, have been frequently used for automated seizure detection using EEG signals. Epileptic seizures give rise to changes in certain frequency bands which are δ (0.4 – 4 Hz), θ (4 – 8 Hz), α (8 - 12 Hz) and β (12 – 30 Hz) [1]. That's why usually the spectral content of the EEG is used for diagnosis [2].

Usually the approach toward the detection of epileptic patterns start with dividing the EEG data in multiple small epochs, then multiple signal processing steps are applied on these epochs to extract out the features which are then used to classify them as epileptic or non-epileptic.

There are almost ten types of epileptic patterns as mentioned by Noachtar et al. patterns like spikes, sharp wave, benign epileptic discharges of childhood, spike-wave complexes, slow spike-wave complexes, 3-Hz spike-wave complexes, polyspikes, hypsarrhythmia, seizure pattern, status pattern are considered as epileptic [7] [8].

Majority of the work done in the line of epileptic pattern detection usually do not involve fusion of information obtained from multiple channels. Instead, all the channels are processed in series/sequentially, as if the EEG signal source is one long signal instead of multiple parallel signals. However Chang et al. [9] appreciated the effects of multiple channels' being processed in parallel. They grouped 0.3 sec epochs of multiple channels simultaneously in five different clusters to avoid noise. Then they applied FastICA to discriminate between features, noise and background of the signal. They then applied DWT with Daubechies-4 (db4) as mother wavelet on the two most independent parts of the signal. Then they applied customized threshold to classify them as epileptic or not. In this work Chang et al. showed that consideration of multiple channels in group improve the accuracy of your system. Xanthopoulos et al. [10] used sliding variance on Continuous Wavelet Transformed (CWT) epochs to detect the clinically important epileptic patterns up to 98.625% accuracy.

Luo et al.'s [11] work advocates the importance of feature reduction techniques like Principal Component Analysis (PCA). He evaluated the effectiveness of six features. PCA showed that almost three of the six features has contribution ratio of 79 %. So discarding of other three features could improve the processing time without a significant damage to the classification accuracy. His stance was verified by the Artificial Neural Network (ANN) classifier whose accuracy only dropped by 2.5% with the exclusion of three features. The six features were Hurst Index, Standard Deviation and Periodicity, Shannon Entropy, Approximate Entropy and periodicity of smoothed EEG signal, where the first three are the most contributing features.

Petersen et al.'s [12] work shows that to detect the generalised seizure using only one channel, usage of the energy of the detail coefficients of the wavelet transformed one second epoch of a F7-FP1 in an SVM classifier can result with as good as 99.1% sensitivity.

In Abdullah et al.'s [13] work Hidden Markov Model (HMM) was applied on vector quantized Stationary Wavelet Transform coefficients of intracranial EEG signal. Their work resulted with 96.38% and 96.82% average sensitivity and specificity respectively. Sousa et al. [14] studied how rhythms analysis identifies the various events recorded in the EEG. Their work resulted with 95.5% accuracy.

Abdullah et al. [15] simultaneously used features extracted from DWT and Fourier transform in an ANN classifier. Their work resulted with 98.889% accuracy.

Khan et al. [16] used energy and normalized coefficients of variance of multi-level DWT coefficients. These features were used by a Linear Discriminant Analysis (LDA) to classify the EEG epochs with an accuracy of 91.8%.

Due to the heavy computational burden of marching pursuit (MP) algorithm [17] proposed a reduce complexity of sparse representation to adopt harmony search method in searching the best atoms. Their efforts resulted with huge amount of improvement in the latency. Wang et al. [18] used these features with Adaptive Neuro-Fuzzy Inference System (ANFIS) as a classifier. Here they integrated the artificial neural networks and fuzzy logic together. Their effort resulted in 97.4% accuracy.

Choi et al. [19] selected the optimal frequency band features by using the Sequential Floating Forward Selection (SFFS) algorithm. These features were fed to three types of classifier. These classifiers were linear, quadratic and cubic discriminant function. They found QDF with best accuracy which was 97.2%.Sezer et al. [20] tested multiple types of ANN and found Elman method to be most accurate along with DWT as feature extraction method.

Alam et al. [21] used the higher order statistical parameters like variance, skewness and kurtosis of empirical mode decomposed EEG signal with ANN.

Seng et al.'s [22] used simple features like mean, variance, dominant frequency, mean of power spectrum and the signal data itself of the EEG epochs in linear SVM. They tried multiple epoch sizes which were 23.6 sec, 11.5 sec, 5.8 sec, and 1 sec. The result showed that smaller epoch size results in better accuracy whereas bigger epoch size results in better latency.

Ocbagabir et al. [23] used Butterworth band pass filter to decompose the EEG signal into 5 sub-bands and then used Energy, Entropy, and Standard Deviation as features for a SVM classifier. This classification approach resulted in 95% accuracy.

Kaleem et al. [24] applied a novel variation of the EMD called Empirical Mode Decomposition-Modified Peak Selection (EMD-MPS). They used Energy, sum of the amplitude spectrum, sparsity of the amplitude spectrum and the sum of derivative of the amplitude spectrum as the input features to a simple 1-NN classifier which resulted with 98.2% accuracy. Murugavel et al. [25] used a novel feature named as Combined Seizure Index as a feature which they extracted from wavelet packet coefficients. These features in a multi scale SVM resulted with 97.3% accuracy.

Majority of the commercially available Neurophysiological Data Analysis software tools are quite generalized for epilepsy diagnostic usage. These tools are a lot user dependant and they are not focused on any specific neurological disorder. Though these tools allow the neurologist to interactively apply multiple signal processing techniques on the EEG data but still neurologists who lack proficient background in signal processing may not feel comfortable using them. None of these tools are intelligent as they don't learn or improve themselves as per neurologist's marking. That is why each time the neurologist has to go through a time wasting fatigue by monitoring lots of useless epochs of EEG data which can be avoided by inclusion of the self improving mechanism in the software so that it may not repeat its mistakes after being pointed out. A huge majority of these software tools are also hardware dependent. They usually come along side the EEG equipment [26] [4] [6] [5] [26].

III. Proposed System

In this paper instead of only introducing a simple epoch classifier we intend to propose a full intelligent neurologist support system which can help a neurologist in diagnostic inspection of epilepsy suspected patient's EEG data. Following is the workflow of our system.

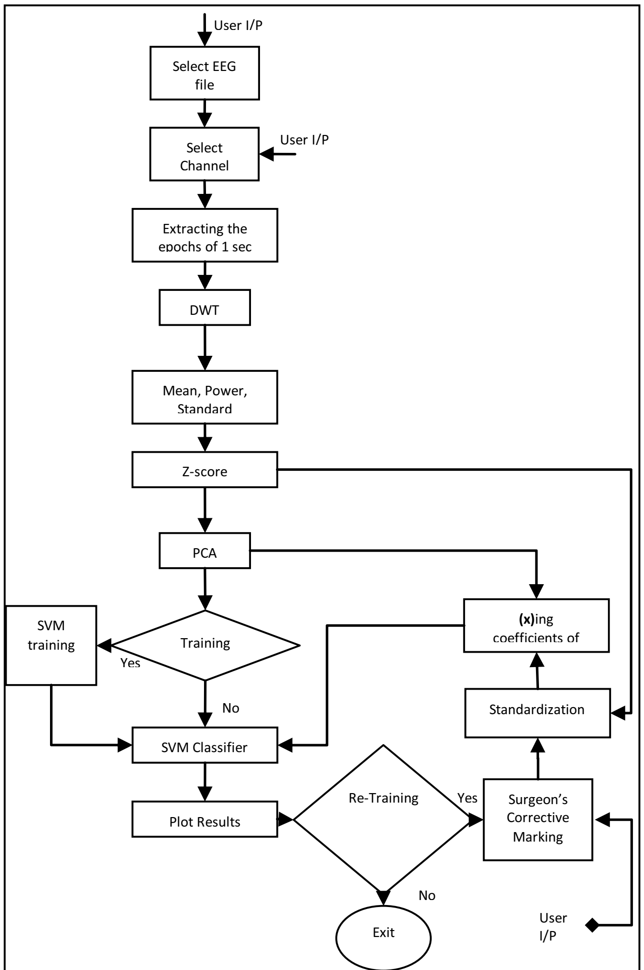

Fig. 1. Workflow

After a user get logged in to our system. He has to load an EEG file and then select a channel which he intends to monitor. After this EEG signal of that channel is then divided into multiple non-overlapping epochs which are then classified as epileptic or not.

A. Features

In our approach we process each epoch of each channel for each type of epileptic pattern exclusively using signal processing and machine learning techniques. We applied DWT on each epoch of a channel and then statistical features are calculated from the selected detailed coefficients. These features are then reduced using PCA and then fed into classifier to classify the epoch as epileptic or not. Following are the details of each step.

1) Epoch size

Epoch is a small chunk of a signal with respect to time. Each Epoch is handled at a single instance. The epoch size which resulted best in our system was 1 sec which re-establishes the work by Seng et al. [22].

2) Discrete Wavelet Transform (DWT)

We applied a multi level DWT on each epoch with Daubechies-4 (db4) as mother wavelet. The detailed coefficients levels of the DWT are determined with respect to sampling frequency.

a) Detail levels

The detailed levels are adjusted on the run according to the sampling frequency such as that we may get if not exact then at least the closest separate δ (0.4 – 4 Hz), θ (4 – 8 Hz), α (8 - 12 Hz) and β (12 – 30 Hz) components of the signal. Any detailed coefficients which does not contain frequency component from a frequency range of 0-30 Hz were discarded.

3) Statistical features

Instead of using all of the detailed coefficients we took the mean, standard deviation and power of each epoch's selected DWT coefficients as suggested by Subasi et al. [27]. After that we applied z-score standardization on these features [28].

4) PCA

Then we applied Principal Component Analysis on these features to reduce them in order to avoid redundant and/or noisy data. We kept the component which projected the 93% of the total variance. The total of 21 features was reduced to 9.

B. Classifier

Then we fed the reduced features to the SVM classifier. These features were used to perform the initial training of the classifier. We found linear to be the best performing kernel with 50 as the box constraint.

Labelling is very important in our system. There is a separate classifier for each channel and each epileptic pattern type. So it makes total of number of classifier as product of number of channels and ten, where ten is the number of epileptic patterns described by Noachtar et al. [7].

C. Display

In our system a user can choose any channel at any time and analyze them. To supplement the user while analyzing the

EEG signal there will be three adjacent windows in the user interface as shown in the following figure.

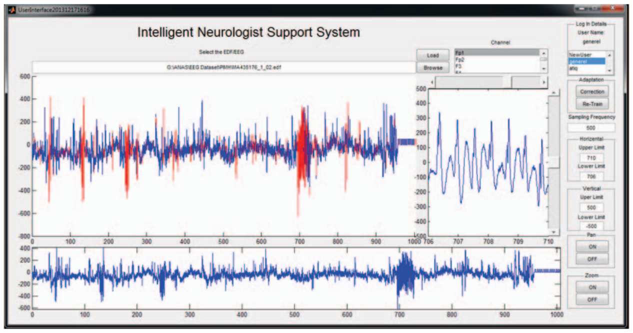

Fig. 2. GUI

1) *Classification-Box Window*

In the top left window which is named as classification window, a user can easily analyse and observe the EEG data of any channel classified by our system as epileptic or non-epileptic. Here the part of the signal marked as "red" is classified as epileptic blue as non-epileptic. By turning on the zoom button a user can zoom in horizontal i.e. time wise and vertical i.e. voltage wise as per his will. To pan the data in vertical or horizontal axis he can turn on the pan. The user can even perform a selective axis zoom or pan by right clicking and selecting the respective option. This gives a user a lot of room while analyzing the details of the signals.

2) *Zoom-Box Window*

But what if a user wants to compare two different parts of the data? To do so there is another window which is placed on the right of the classified window. This window has slider on both of its axis which allows the user to perform a fine pan. Whereas on the right of this zoom box the user can manually input the vertical or horizontal axis value, or voltage on time values which he want to analyze.

3) *Summary-Box Window*

To keep a track of the whole signal, there is another window which displays the summary of the whole of the EEG signal of the selected channel. That window is placed in the bottom of the user interface.

D. *Corrective Markings*

A very important and relatively novel part of our system is user adaptation mechanism. It is been cited that some time even the expert neurologist have some disagreement over a certain observation of an EEG data. There is also a threat of over fitting by the classifier. In order to keep the classifier improving its performance with the encounter of more and more examples, we have introduced a user adaptive mechanism in our system.

When a user clicks the correction button he can interactively select epochs from any of the three windows of his choice. The selection will prompt a confirmation window which will confirm the details of the disagreement. These details include user name, channel number, epileptic pattern indication, start and end of epochs. The user name will let the system adapt itself to the user and as planned in future if we can make this available on the internet then multiple expert neurologists can compare their marking with possible markings of other neurologists by few clicks for a same subject.

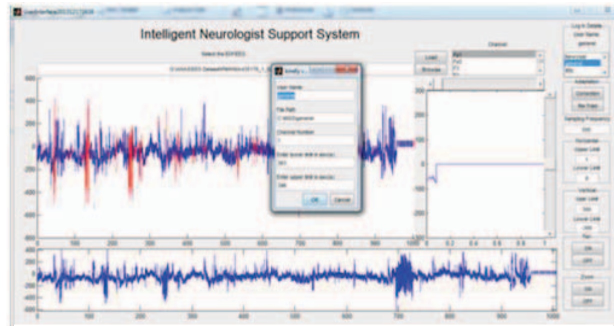

Fig. 2. Corrective Marking

a) Logs

These details will be saved in a log in the background and they will be used to retrain the classifier to improve its classification rate and adapt itself according to the user with the passage of time. When the user is going to select the retraining the system's classifiers will re-train themselves.

E. *Retraining*

When the retraining button is selected, the classifiers will be retrained on the previous and the newly logged training examples.

F. *Data Management*

Data Management is very important part of our system. There are some certain amounts of feature data we will always have to keep in our system. This data is based on files which contain the features of multiple epochs of EEG which are important for training a classifier.

1) *PCA for reducing the training examples*

Then we applied PCA to reduce the training examples. We kept examples which defined the 98 percentage of the total variance.

a) PCA for reducing the examples

As there is not any infinite space available to store the training examples so after every re-training PCA is applied on the stored data and the new components with 90% of the mixture model are left and the rest are discarded so that number of the training example can be maintain up to a certain limit.

IV. RESULTS

In this section we will discuss the results in detail. At first we will describe the datasets which are used to test and validate our method. Then we will discuss the versatility they caused in at different important steps of our method.

A. *Data set*

The Datasets available to us were about generalised absence seizure which is identified by the 3Hz spike and wave epileptic pattern in almost each channel. That is why we have classification results available only for one type of epilepsy which is absence seizure.

1) CHB-MIT

This EEG database is the online available CHBMIT scalp EEG database [29]. It been provided by Children Hospital Boston and is available at physionet website [30]. This database consists of 916 hours of continuous scalp EEG recordings collected from 24 subjects suffering from intractable seizures. Out of 664 EEG recordings files, 129 files consisted of one or more seizures. The 23 channel EEG signal has a sampling frequency of 256 Hz with 16 bit resolution.

2) PIMH

The second database of EEG datasets is provided by our collaborator at Punjab Institute of mental health (PIMH), Lahore. It was sampled on 500 Hz and it was recorded on 33 channels. This dataset consists of 21 patient's EEG recording.

B. Features

We build exclusive classifier for each channel and each epileptic pattern so for exclusive 22 channels (as 23rd was same as 15th) of CHB-MIT database we had to be built 220 classifiers where 33 channelled PIMH dataset 330 classifiers were built.

Our data of interest lies in between the frequency range of 0.3Hz to 30Hz. So after application of DWT we have to select detailed coefficients with in this frequency range. In case of 256 Hz sampled CHBMIT dataset we have to go to at least 3 levels of decomposition. The coefficients which contained the frequency component of 33 – 256Hz were discarded. In order to get the discriminating information between different types of epileptic patterns and identifying them correctly without mistaking it with each other, decomposition of this detailed coefficient further in Beta, Alpha, Theta and Delta will be hugely help full. In order to do so we further decomposed them until the 7th level. So, we used the DWT's detailed coefficients of level 3,4,5,6 and 7 while for 256 Hz sampled CHB-MIT dataset.

TABLE I. THIS TABLE DESCRIBES THE AFFILIATION OF DETAILED COEFFICIENTS WITH EPILEPTIC FREQUENCY BAND OF INTEREST FOR 256HZ SAMPLED CHBMIT DATASET

Epileptic Frequency Range	**Detailed Coefficients' level**
Beta **(β)**	CD3 (32Hz to 16Hz)
Alpha **(α)**	CD4 (16Hz to 8Hz)
Theta **(θ)**	CD5 (8Hz to 4Hz)
Delta **(δ)**	CD6 (4Hz to 2Hz)
Delta **(δ)**	CD7 (2Hz to 1Hz)

In case of 500 Hz sampled PIMH dataset we used the DWT's detailed coefficients of level 4,5,6,7 and 8.

TABLE II. THIS TABLE DESCRIBES THE AFFILIATION OF DETAILED COEFFICIENTS WITH EPILEPTIC FREQUENCY BAND OF INTEREST FOR 500HZ SAMPLED PIMH DATASET

Epileptic Frequency Range	**Detailed Coefficients' level**
Beta **(β)**	CD4 (31.2Hz to 15.6Hz)
Alpha **(α)**	CD5 (15.6Hz to 7.8Hz)
Theta **(θ)**	CD6 (7.8Hz to 3.9Hz)
Delta **(δ)**	CD7 (3.9Hz to 2Hz)
Delta **(δ)**	CD8 (2Hz to 1Hz)

C. SVM classifier

We used 10-fold validation method. We took ten random distribution of the data set and recorded the average of the classifier's performance. 8736 epochs were used to validate our approach. These 8736 epochs were randomly taken from 24 patients from CHB-MIT dataset and 21 patients from PIMH dataset. In this method we took ten random distribution of the data set and recorded the classifier's performance.

We found *"linear"* to be the best performing SVM kernel with 50 as the box constraint. The initial training of the classifier resulted with 94.8% average accuracy, 95.7% average specificity and 91.7% average sensitivity. Due to unavailability of the data currently we have only classification rates for generalized absence seizure. After initial training our specificity is better than the Shoeb et al. and Nasehi et al. [30] [31].

The processing of the each channel exclusive to each other improved over average accuracy from approximately 91 % to approximately 95%. So there is a significant improvement of 4% by introduction of this change.

The concept behind the inclusion of the retraining is that, if there is more than one example with same attributes but different labels, the classifier is going to get trained to the one with most population. The user's marking will increase the examples of his choice thus making that classifier adapt itself to the user's choice in a simpler way. Every user will have exclusive classifiers trained for him and his marking will not affect other user's classifier. Our system have shown that after correction of as low as 269 epochs there was a visible improvement in the system's classification. The average accuracy of the system rose from 94.8% to 95.12%.

V. CONCLUSION

Epilepsy is an important neurological disorder. Computer assisted analysis of EEG for diagnosing Epilepsy significantly helps a neurologist. To avoid misinterpretation and over-interpretation a computer assisted system should be user friendly, accurate, robust and above all informative. Lots of work has been done in this regard. With the addition of our suggested steps in the existing work robustness and the classification accuracy can be improved.

In future we are planning to integrate the video alongside this interface, as the analysis of video EEG can help a neurologist in diagnosing epilepsy in better way whereas this can also help him in distinguishing between psychogenic and epileptic seizures.

Other then video integration we are also planning to make this a web based application so that neurologist can login and consult each other's reviews about a particular subject. This will make our system experience a whole versatile of examples and learn from all of them.

In some particular conditions number of these classifiers has been cited to perform with 100% accuracy. This accuracy is probably a result of over-fitting as same techniques when applied on real life data do not result with such high accuracy. So there should be method which should keep these algorithms improving their detection with increment in the available examples. There should be a method introduced where a neurologist can suggest corrections as per his desire while observing wrong marking by the computer aided system and the system should learn from that correction.

Our proposed system is more like a personal Neurologist support system. Right now in the current proposed system the by personalizing we meant the classifiers classification as per user desire. This system is made keeping in mind that we have to facilitate the neurologist by supplementing him in the analysis of the EEG. We do not want to enforce the classification of the EEG data on a user.

Our result is tested on the most versatile data set and its high average accuracy for different type of datasets clearly shows its robustness.

ACKNOWLEDGMENT

Here we will like to acknowledge Dr. Rizvi and his institute PIMH for providing us the assistance in collecting the real life dataset from PIMH.

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