Automated Statistical Data Mining of a Real World Landslide Detection System

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Abstract—*Wireless sensor network for landslide detection deployed in Munnar consists of 150 geophysical sensors which are spatially distributed over 20 Deep Earth Probes (DEP) located at different areas in the deployment site. The data received from each of these heterogeneous sensors are mined to retrieve the correlation between the various parameters contributing to landslide, using appropriate statistical methods. This paper presents an architecture which we have developed for automatic data mining of landslide data which will ultimately help in issuing an early warning for occurrence of landslides. Several algorithms were developed towards achieving this objective of effective data analysis of the continuous real time data collected from the deployment field. The results show that the slope instability in a region is dependent not only the intensity of rainfall but also the antecedent rainfall conditions and soil layer parameters. Each of these different algorithms and its results are explained in detail in this paper.*

Keywords- Landslide, statistical data analysis, pore pressure, rainfall rate, slope instability.

1. Introduction

Landslide is the third most deadly natural disasters on earth and it can be triggered by gradual processes such as weathering, or by external mechanisms like soil erosion, prolonged rainfall, earthquakes, floods, morphological factors like slope angle, physical factors like volcano eruptions etc. Reports show that 17% of disasters occur due to landslides which lead to considerable loss of life and damage to communication routes, human settlements, agricultural fields and forest lands [1]. So it is important for us to early warn the occurrence of landslides for saving lives, property, etc. For detecting landslides, Amrita Center for Wireless Networks and Applications has developed and deployed world's first ever wireless sensor network for landslide detection in Munnar, Kerala, India. Huge amount of data are received in the Data Management Center at the Amrita University from various sensors deployed in the DEPs for monitoring those factors contributing to landslide.

Munnar, the south-east area of Kerala experience several types of landslides, of which debris flows are the most common. Studies conducted in the area indicates that pro-longed and intense rainfall or more particularly a combination of the two and the resultant pore pressure variations are the most important trigger of landslides in that area [8]. Suitable statistical techniques have been employed for analyzing the inter-dependability of these factors and thereby effectively determining the pattern for pore pressure buildup. Based on Richard Iverson Equation [6],[11], permeability, hydraulic conductivity and depth are some important factors which influence the pore pressure build up in soil. Hence our dataset contains information about pore pressure, rainfall rate, depth of each sensor in the DEP, permeability, hydraulic conductivity, antecedent conditions of rain, etc. We have developed algorithms incorporating relevant statistical techniques which will take these parameters as its input, for identifying the correlation between them. These data mining algorithms form an integral part of the automatic data analysis system which we have designed for the Landslide detection system in Munnar.

The remainder of the paper is organized as follows. Section II describes related works in data analysis. Section III delineates the heterogeneous data from landslide detection system. Section IV explains the architecture of automatic data analysis. Section V presents the statistical analysis and the algorithms developed. Section VI deal with the experimentation and evaluation of the proposed algorithms. Finally, we conclude and outline the future work in Section VII.

2. Related work

Large numbers of sensors are deployed in Wireless Sensor Network for Landslide Detection at Munnar and the correlation between these huge data plays an important role in landslide detection. Developing algorithms for determining these correlations by analyzing real world data is a challenging job.

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Similar work has been identified to be done in cases like thunder storm prediction [2] and slope instability analysis [3]. Paper [2] presents the multiple correlations in the data from thunderstorm and application of these correlations in the prediction of seasonal severe thunderstorms using K-nearest neighbor (K-nn) method, and modified K-nn method. Recently, object-oriented analysis (OOA) is implemented on the data from Light Detection and Ranging (LiDAR) for the landslide identification [4]. Another study is done to examine the long-term parameters in order to define their relations to landslide occurrence [5]. Paper [15] explains statistical analysis of landslide area in the Daunia area, Italy using data from GIS technology. Linear regression method is used for produced a reliable susceptibility map of the investigated area. Topographical/geological data and satellite images were collected and processed using GIS and image processing tools and these data were analyzed and used for landslide hazard mapping in Cameron Highland, Malaysia[16]. Soil properties and rain fall rate are also important factors in their analysis. Basically studies have been done on image data from landslide area which may not be an accurate method for prediction. Complexity of our work lies on the fact that our work deals with the continuous real data from 2009 onwards to till date. Also it is difficult to generalize the factors affecting pore pressure because the soil properties vary with different locations.

Since the deployment area is known for rainfall induced landslides, the proposed data analysis methods concentrate on the analysis of rainfall rate and pore pressure values and find the impact of rainfall on pore pressure buildup.

3. Heterogeneous data from landslide detection system

A wireless sensor network (WSN) for landslide detection is deployed in Munnar. The system is used for continuous monitoring of environmental, geological and hydrological parameters that may trigger a landslide. The real-time data from this system is used for early warning of landslides.

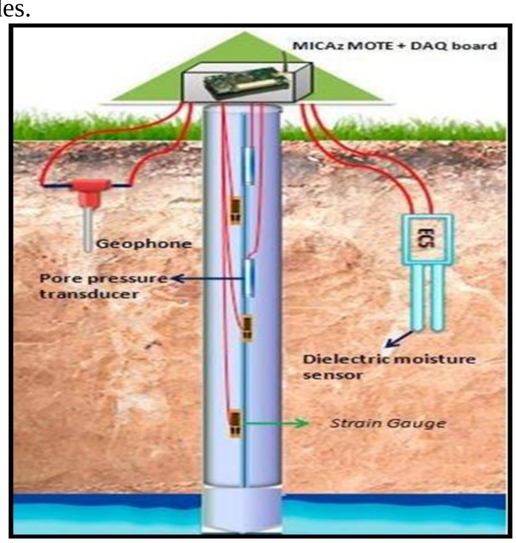

Fig. 1. Enhanced Sensor Column Design [8]

The rainfall induced landslides can be triggered due to heavy or continuous rainfall, increased soil moisture content, rise in pore pressure, excessive weathering, earth quake, toe removal by humans etc. Heterogeneous sensors such as rain gauges, moisture sensors, pore pressure sensors, strain gauges, tilt meters, geophone etc., are deployed to monitor the above parameters. These sensors are attached to a Deep Earth Probe (DEP) as shown in Figure 1.

Currently 20 DEPs are deployed in the landslide prone area as shown in Fig 2. The spatial variability of DEP deployment is dependent on the spatial vulnerability of landslides. Hence the location of DEP deployment is dependent on the site specific geological conditions.

This landslide detection system has a total of 150 geophysical sensors connected to these 20 DEPs. The sensors connected in each DEP is determined by considering various factors such as soil layer structure, soil properties, different parameters to be monitored in each soil layer etc. Hence each DEP consists of multiple types of heterogeneous sensors at different soil layers, at different depths. This contributes to spatial variability of the features and hence each DEP gathers unique information. This system provides the opportunity to collect the real-time data dynamically in any frequency. Currently the sensor data is collected at the rate of one sample per minute and stored in the database.

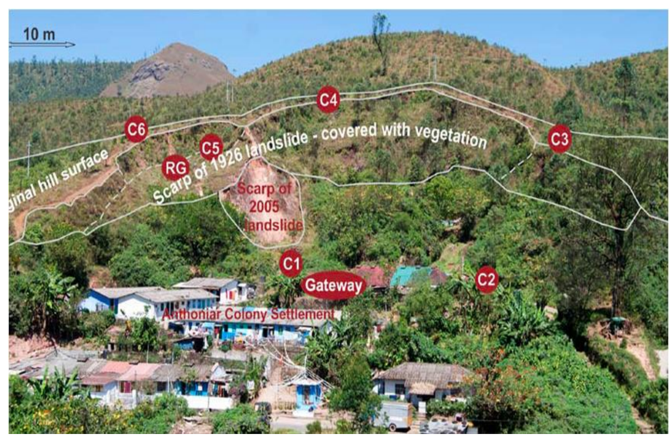

Fig. 2. Locations of the DEPs and Rain Gauge (RG) [9]

4. Architecture of automatic data analysis system

For better forewarning of landslides, identification of inherent relation between landslide parameters are necessary. One of the objectives of this work is to identify the relation between the data from the Wireless Sensor Network System for Landslide Detection deployed at Munnar. Using the knowledge gained from the data mining and data analysis, this system will be equipped to predict the risk levels of landslides and issue early warnings to the community at the deployment area.

For the current deployment, the geophysical sensors are spatially distributed based on many factors such as the number of soil layers, layer structure, soil properties and variability, hydraulic conductivity of the soil layers, the presence of impermeable layers, the water table height, the bed rock location, depth of the bore hole for deploying the DEP, and the specific deployment method required for each geophysical sensor. Hence the data received from these sensors has to be analyzed considering some of the above factors.

The architecture diagram for automatic data mining and analysis is shown in Figure 3.The heterogeneous data received from multiple sources like WSN, terrain mapping, soil properties, and weather forecast are collected in the database. The pore pressure values and rainfall rate are the main contribution of WSN whereas the terrain mapping gives the spatial data. Soil properties include information such as permeability, hydraulic conductivity, etc. and the data from these multiple sources along with the weather forecast data is used for the learning purpose. The entire data is stored in a database. This data is analyzed using different statistical algorithms. The output of data analysis is given to the knowledge base and also as input to the learning algorithms. The pore pressure buildup is predicted on a spatio-temporal basis after the training and testing process in the learning phase by using a suitable machine learning algorithm. The Factor of Safety (FoS) is then calculated from the predicted pore pressure values. The occurrence of landslide is specified using different risk levels which is based on the calculated FoS value. Based on this risk levels, alert dissemination to the local community is done.

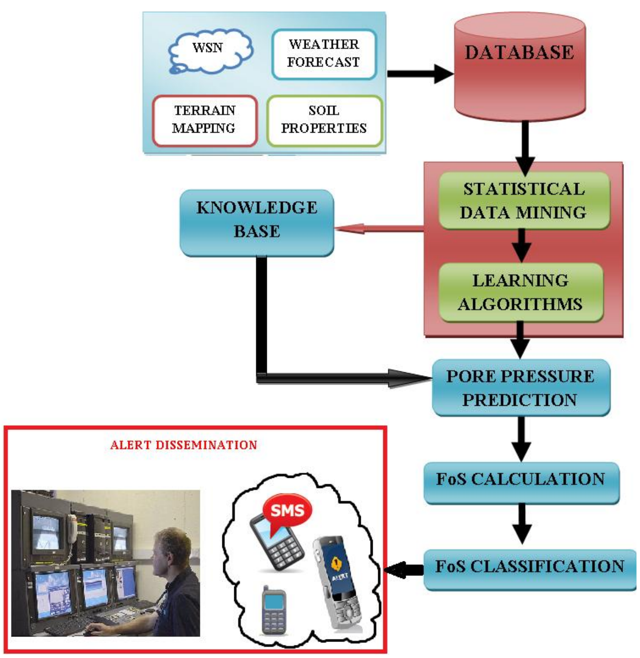

Fig. 3. Proposed System

5. Statistical analysis and its algorithms

Slope instability in rainfall induced landslides is majorly triggered by continuous rainfall or instant heavy rainfall. As the rainfall increases, the pore pressure at each soil layer will build up with respect to the soil structure, its soil properties, vegetation etc. As the pore pressure increases, the cohesion between the soil particles decreases, leading to slope instability. The slope instability [7] can be determined by calculating the FoS of the slope [19].

$$\mathrm{FoS} = \frac{C + (\sigma - \mu)\tan\phi}{\gamma z \cos\beta \sin\beta} \tag{1}$$

$$= \frac{C + (\gamma - m\gamma w)\, z\cos\beta\cos\beta\tan\phi}{\gamma z \cos\beta \sin\beta} \tag{2}$$

In equations (1) and (2), C is the cohesion in kN/m^2, γ is the unit weight of slope material in kN/m^3, γ_w is the unit weight of water in kN/m^3, z is the thickness of slope material in m, m is the vertical height of water table above the slide plane, and is dimensionless, β is the slope of the ground surface in degrees, φ is the internal angle of friction in degrees, σ is the normal stress, and μ is the pore water pressure. The increase in rainfall causes increase of pore pressure, leading to the decrease of FoS of the slope. The chances of slope instability increases as the FoS become less than 1.

The conditions leading to the instability of the soil layer has to be continuously monitored, analyzed and the inference has to be derived for an effective early warning system. Hence it is highly necessary to continuously analyze the data received from rain gauge and pore pressure sensors and derive the state of the hill slope. For achieving this objective we have developed several algorithms for data mining the continuous data collected from the deployment field.

Initially data cleaning is done in the input dataset in order to remove the noisy data. In this phase the historic data will be mined to remove any outliers and other noisy data. This cleaned data is then stored in the database.

To determine the effect of rainfall on inducing landslides, it is highly necessary to determine the correlation among the heterogeneous sensor data and identify patterns leading to slope instability. In this work, we are mainly concentrating on the impact of rainfall rate on spatio-temporal pore pressure build up in the landslide prone area. For determining patterns of rain and effect of rain on pore pressure build up, the following algorithms are developed to perform the data mining.

5.1 Classification of rainfall

Instant rainfall conditions along with antecedent rainfall conditions lead to slope instability. The research papers [10], [14] describe the effect of antecedent rain on pore pressure build up. Hence thorough analysis of rainfall data is essential to determine the patterns of rainfall. The algorithm for classification of rainfall is described below. This algorithm consists of three phases as described below.

- Rainfall rate per day: The cumulative value of rainfall data will be determined from the available rainfall data per minute with respect to each day.
- Rainfall rate per multiple days: The cumulative rainfall data for one day, two day, up to 15 days are found and stored in the database with respect to each day.
- Rainfall classification: By using existing classification techniques, the results of the above phases such as rainfall rate per day and rainfall rate per multiple days, will be used to classify the rain data as instant heavy rain, continuous rain, continuous heavy rain, and no rain.

The classification of rain data is used for determining the effect of each class of rainfall on pore pressure build up.

Algorithm1: Analysis of rainfall

Input: Rainfall in millimeter from database
Output: Date of rainfall, cumulative rain data in millimeter, and classes of rain.

1. Retrieve the rainfall_rate from database.
2. *count_of_rainy_day* = 0
3. For each day:
4. cumulative_rainfall=$\sum_{i=1}^{p}$ rainfall_rate
5. *IF* cumulative_rainfall=0
   THEN label="No_rain"
6. *ELSE*
   $$\text{Total\_rain}=\sum_{j=1}^{\text{count\_of\_rainy\_day}} \text{cumulative\_rainfall}_j$$
7. *IF* count_of_rainy_day>1
   THEN label="Continuous_rain"
8. *ELSE*
   Label="Rainy day"
9. *IF* cumulative_rainfall>dynamic_threshold
   THEN Label="Instant_heavy_rain"

5.2 Spatio-temporal analysis of pore pressure data

In each DEP, multiple pore pressure sensors are deployed at different depths. The data from these pressure sensors, implanted at different locations in each DEP located at various geographic locations, are continuously collected. These data are analyzed for determining the inherent spatio-temporal correlations that exist among pore pressure values. These correlations play a vital role in early warning of the risk levels of landslide. The algorithm for spatio-temporal analysis of pore pressure data is described. This algorithm consists of three phases as described below.

- Mean of a Day: In this phase the historic data is used to determine the mean per day for pore pressure sensor values at different depths and different locations.
- Variance of a Day: In this phase the historic data is used to determine the variance per day for pore pressure sensor values at different depths and different locations.
- Maximum of a Day: In this phase the historic data is used to determine the maximum value per day for pore pressure sensor values at different depths and different locations.

Algorithm2: Behavior of pore pressure builds up of Piezometer

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Input: Pore pressure values and DEP details from database
Output: Maximum, mean and variance of pore pressure values of each piezometer in a particular DEP in daily basis.

1. Retrieve DEP_Group_No from DEP details and pore_pressure_value from database.
2. For DEP_Group,
3. For i=0 to No_piezometers
4. Piezo_field_name[i]={DEP_Group_No, piezometers_name[i], depth}
5. Let Max_Pore [] =ϕ
6. For each day:
7. For j=0 to No_piezometers
8. For k=0 to No_of_pore_values
9. IF Max_Pore[k] <pore_pressure_value
10. THEN Max_Pore[k] = pore_pressure_value
11. $$\text{Mean\_pore}=\frac{\sum_{p=0}^{\text{No\_of\_pore\_values}} \text{pore\_pressure\_valuere}_{p}}{\sum \text{No\_of\_pore\_valuere}_{p}}$$
12. Variance_pore=
$$\frac{\sum_{p=0}^{\text{No\_of\_pore\_values}} (\text{pore\_pressure\_valuere}_{p} - Mean\_pore)2}{\sum \text{No\_of\_pore\_valuere}_{p}}$$

The results obtained from these phases are used for further statistical analysis and inference generation. The behavioral pattern of pore pressure values obtained from different depths of each DEP and also from different DEPs could be used to determine the real-time infiltration rate. This could also be used for correlating the effect of amount of rainfall, the duration of rain, soil structure and the depth on infiltration rate.

5.3 Potential vulnerable zone identification

During rain, the water will infiltrate through the permeable soil layer structure and percolate down through each of the layers. This will build up the ground water level. However soil layers differ in their permeability. In some cases intermittent soil layers can be impermeable. The water cannot seep out through the impermeable layer at the same rate as that of the permeable layer, leading to the development of perched water table. This will loosen the soil particles and cause slope instability. Hence monitoring this phenomenon is necessary for early warning of landslides.

The maximum pore pressure value per day can be calculated using the Algorithm 2. Using this detail along with the DEP details will provide the opportunity to learn the variance of pore pressure values in a DEP. This will help us to understand how the pore pressure build up differ with respect to depth of pore pressure sensor deployment, soil structure, and soil properties. The layer at which pore pressure value is high compared to its lower layer is one of the indications of vulnerable zone. The detailed verification of the presence of vulnerable zone, and its causes are explained in the Algorithm 3.

Algorithm3: Determination of the "vulnerable zone"

Input: Maximum pore pressure data on daily basis from knowledge base
Output: Vulnerable zone

1. Retrieve the depth of piezometers from DEP details from knowledge base
2. Compare the depth of piezometers in each DEP
3. Check whether increasing order
4. Compare the maximum pore pressure value with respect to the depth order
5. IF it follows the same order
   THEN "*Normal zone*"
6. IF irregularity in pore pressure value
   THEN "*Potential Vulnerable zone*"
7. Check the soil properties
8. IF permeability low,
   THEN "*Vulnerable zone*"

5.4 Spatio-Temporal Correlation of Rain and Pore Pressure Data:

The spatio-temporal correlations of rain and pore pressure data play a vital role in changing the risk levels of landslide. The data mining results obtained using the Algorithms 1 and 2 will be used to retrieve the inherent information of slope instability process. The rainfall classification, cumulative rainfall, maximum pore pressure, mean pore pressure, and variance of pore pressure for different time scales and space scales are used to derive the knowledge and patterns necessary for early warning of landslides.

Each DEP contains a maximum of eight pore pressure sensors at different depths. The behavior of pore pressure build up depends on soil properties, position of water table, and current and antecedent conditions of rain [13]. If the pore pressure builds up goes beyond the threshold value, the cohesive force between the soils will be reduced and landslide occurs. Hence the pore pressure is analyzed with respect to rainfall rate to identify and learn the specific behavior pattern of pore pressure build up, patterns changes due to the impact of soil structure, soil properties, hydraulic properties etc.

By analyzing the outputs, we found that the pore pressure build up depends on the amount of rainfall, the duration of rain, soil structure and the depth. In order to determine the time duration which makes pore pressure build up by the impact of each rain, we had done further analysis of the data.

6. EXPERIMENTATION AND RESULTS

The real-time data from this system is continuously collected from 2009 onwards. As of March 2014, the system has continuously collected around 100Million observations, with 60 features including piezometer readings, DEP details, rainfall reading etc from 150 geophysical sensors. The complete data from the dataset is analyzed using different scenarios in order to determine the correlations between them.

As discussed earlier, this study is mainly concentrated on two factors viz. rainfall rate and pore pressure values. Those data are capable to capture the initial triggers and indications of slope instability. Hence in this work, rain gauge and pore pressure sensor's data along with soil properties are used for developing the early warnings. Thus the entire number of feature is reduced to around 30 numbers which forms the initial step of dimensionality reduction of the dataset. These observations from the reduced feature set are then aggregated using suitable statistical methods explained above for further dimensionality reduction and thus reduced to around 1lakh observations.

Using Algorithm 1, the rainfall rate of 2011 and 2012 are analyzed in order to identify the pattern and intensity of rainfall at different times in a year viz. 'no rain' season and 'rainy' season so that it can be used for analyzing the effect of the antecedent rainfall conditions on the pore pressure value. The data analysis was mainly performed by focusing on the data from these rainy periods and the correlations are analyzed based on the time duration of the 'rainy' and 'no rainy' days and also the intensity of rainfall during the 'continuous rainy' days. The cumulative rainfall and maximum pore pressure values of DEP group1 on daily basis for the period of October - November 2012 is shown in fig 5. The highest rain in this season is 24 mm and is on 8th of October.

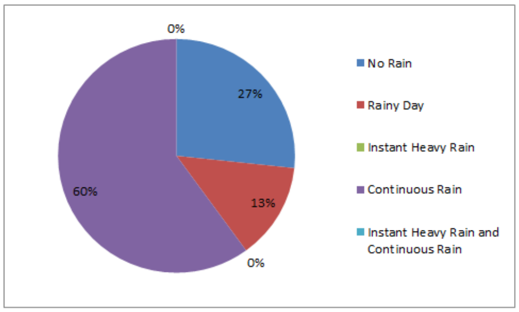

Fig.4. Rain data classification for Oct-Nov 2012

The highest values of pore pressure for *piezo3* at depth 3.3m, *piezo5* at depth 5.5m, *piezo4* at a depth of 8.5m are

22kPa on 20th of October, 140 kPa on 25th of October and 40 kPa on 24th of October. From the graph, it can be inferred that the impact of highest rainfall rate on each pore pressure value occurs after some duration as water takes some time to percolate down from one layer to the other. This is dependent on the depth of the deployment, soil structure, soil properties, and the rate of rainfall and its antecedent conditions. The value of *piezo5* and *piezo3* increase after 12-14 days where as the *piezo4* shows sudden reaction due to the rainfall.

The effect of different rain conditions such as no rain, continuous rain, and instant heavy rain etc., on the infiltration rate is shown in Fig. 6. The graph shows the pore pressure value of the piezometer *piezo1* in DEP group 5 and the rainfall rate during the period of October 2012. During this period, the highest rainfall rate of 24 mm occurred on 8th of October. There was an increase in pore pressure as a result of this rainfall and the value gradually decreased as the rainfall rate dropped. From 9th to 31st October, the rainfall value was almost negligible and it can be seen that the pore pressure value starts decreasing during that period because of the no rain state. As the soil structure vary with the depth, the water infiltration rate in each depth also varies. The results of Algorithm 2 showed that for the same rainfall rate, the effect on each piezometer is seen at different days because of the variation in infiltration rate.

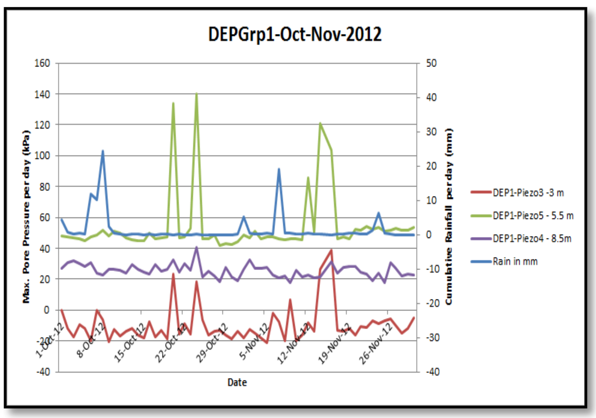

Fig.5. Rainfall rate and Pore Pressure values of DEP1 in Oct-Nov-2012

The deepest piezometer must have the highest pore pressure since it will be below the water table and according to this, the deepest piezometer i.e. *piezo4* at 8.5m must have highest value. But from Fig. 5, it can be seen that *piezo5* at 5.5m shows highest values than *piezo4* and it may be due to the presence of some other water source at 5.5m. Thus the result of Algorithm 3 shows the presence of a vulnerable zone at the position of pore pressure sensor 5 which shows the highest value among all the sensors deployed in that location.

The spatio-temporal analysis of pore pressure value and rainfall rate are shown in figure 7. It contains 5 DEP groups located at different locations and piezometers are deployed in those DEPs at different depths. 5 piezometers are deployed in DEP group1, DEP group 2 contains 3 piezometers, DEP group 4 contains 1 piezometer and DEP group 5 contains 3 piezometers. The graph shows the cumulative value of rainfall and its corresponding maximum pore pressure values for each piezometer deployed in each of the DEPs at different locations during the period of October-November 2012. As mentioned earlier, the highest rainfall rate in this period is 24mm and is on 9th October. The impact of this rain on each piezometer is different. A sudden rise can be seen in *piezo1* and *piezo3* of DEP group5 while *piezo5* of DEP group1 and *piezo1* of DEP group4 shows a rise in its value after 15-18days due to the impact of the same rain. Similarly, *piezo1* and *piezo2* of DEP group2 and *piezo2* of DEP1 show a small rise in 2-3 days whereas *piezo5* and *piezo3* of DEP group1 shows its peak values after 15-18days and *piezo1* of DEP group4 shows a small rise after the same duration. This shows that not just the antecedent conditions of rain alone causes a rise in pore pressure, but it depends also on soil structure & properties as well, because of which some soil layers may have the capability to retain moisture which is why they show an increased rate of pore pressure buildup. Thus by analyzing this graph, we can conclude that the pore pressure build up is also dependent on the depth at which the sensor is placed, the soil structure, duration of the rain and the antecedent condition of rain.

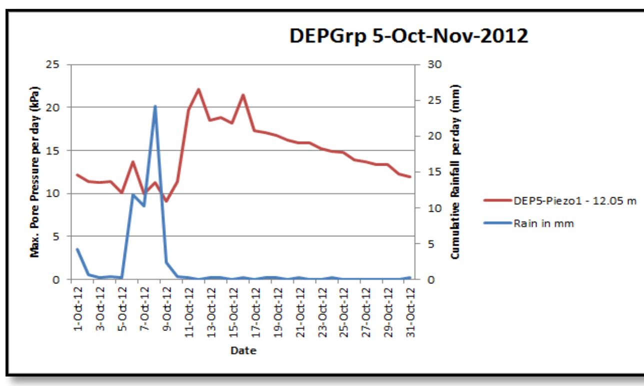

Fig. 6. Rainfall rate and Pore Pressure values of DEP5 in Oct-Nov-2012

7. Conclusion

Determining the relationship between pore pressure and rainfall rate is a challenging and complex process as it is not linear in nature. The proposed system for automatic data analysis of landslide detection system helps to establish the correlations between rainfall and the resulting pore pressure build up in a reasonably accurate manner by taking into account the different spatio-temporal parameters which impacts the occurrence of landslides.

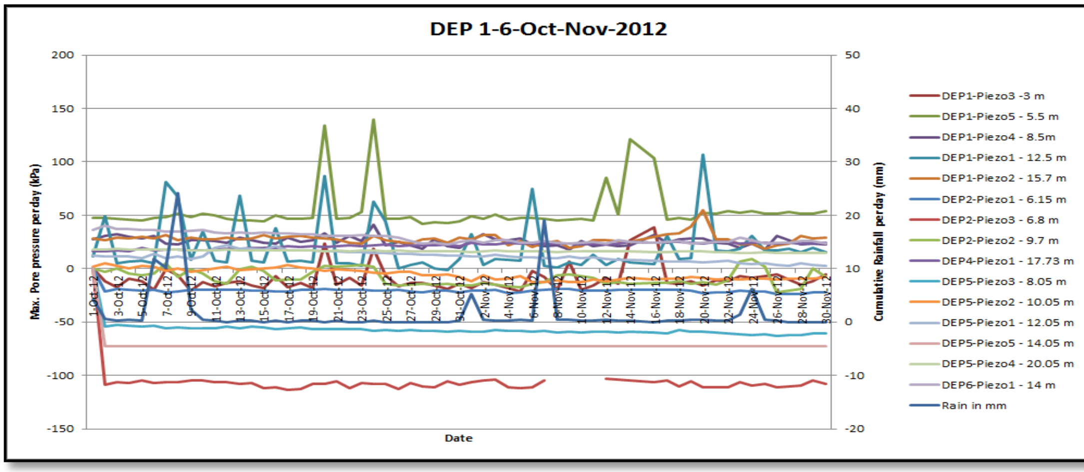

Fig. 7. Rainfall rate and Pore Pressure values of DEPs in Oct-Nov-2012

Through this work we aim to develop an early warning system for landslides by implementing several data analysis and learning algorithms which involves thorough analysis and training of the dataset to detect slope instability based on the pore pressure buildup and presence of vulnerable zones, as well as forecast the risk levels of landslide occurrence. As a future work, we are planning to include the readings from other sensors also like moisture sensor, tilt meter, strain gauge, etc to find the interdependence between each of these parameters thereby developing a more reliable and efficient system which is capable of fore warning the occurrence of landslides.

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