11TH INTERNATIONAL SYMPOSIUM FIELD MONITORING IN GEOMECHANICS

Extracting knowledge on slope behaviour from acoustic emission measurements

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Abstract

Early warning systems for slope instability need to alert users of accelerating slope deformation behaviour to enable safety-critical decisions to be made. Field trials of acoustic emission (AE) monitoring of slopes have demonstrated conclusively that generated AE rates are proportional to slope deformation rates, and AE monitoring can be an effective approach to detect accelerating movements and communicate warnings to users. AE is becoming an accepted monitoring technology for geotechnical applications; however, challenges still exist to develop widely applicable interpretation strategies. In this paper, data from a field trial at Hollin Hill, North Yorkshire, UK and a large-scale experiment are used to develop strategies to extract knowledge on slope behaviour from AE measurements. Machine learning approaches for automated interpretation (warning trigger levels and quantifying rates of slope movement) are developed and demonstrated. A conceptual framework for extracting knowledge from AE measurements for use in decision-making is presented.

Keywords: Acoustic emission, Field instrumentation, Landslides, Machine learning, Monitoring, Slope stability

1. Introduction

Rainfall-induced slope failures cause significant damage to infrastructure and kill thousands each year. It is established practice to monitor slopes to alert users of accelerating deformation behaviour, enable evacuation of vulnerable people, and conduct timely maintenance of critical infrastructure; these are termed early warning systems (EWS). Alarm systems are a category of EWS that provide a timely alert to people in the immediate vicinity of a slope so that responsive action can be taken. The standard landslide velocity scale (Cruden and Varnes 1996) comprises a series of classifications that progress from 'extremely slow' (millimetres per year) to 'extremely rapid' (metres per second), and each classification is separated by two orders of magnitude (Table 1). Acceleration is how rapidly a slope progresses through velocity classifications, and whether the slope is slowing down (decelerating), and hence provides valuable information for use in EWS and risk management.

Velocity class	Description	Velocity* (mm/hr)	Response
7	Extremely rapid	20,000,000	Nil
6	Very rapid	200,000	Nil
5	Rapid	2,000	Evacuation
4	Moderate	20	Evacuation
3	Slow	0.2	Maintenance
2	Very slow	0.002	Maintenance
1	Extremely slow	< 0.002	Nil

*Velocity classifications were rounded to one significant figure (e.g. 0.18 mm/hr became 0.2 mm/hr).

Table 1: Landslide velocity scale (modified after Cruden and Varnes 1996; Hungr et al. 2014)

Acoustic emission (AE) are high-frequency stress waves that propagate through materials surrounding the generation source. In soil, AE is generated by inter-particle friction and hence the detection of AE is an indication of deformation (Smith et al. 2019). AE is becoming an accepted monitoring technology in geotechnics (e.g. Smith et al. 2014; Dixon et al. 2018; Mao et al. 2018); however, there is a dearth of published work by others due to a limited number of groups working in the area globally – the authors would encourage more researchers to join to advance AE monitoring in geotechnics. Recent advances have been made in the development of quantitative AE interpretation strategies for use in landslide early warning and smart geotechnical asset management systems. This paper describes the evolution of these quantitative AE interpretation frameworks.

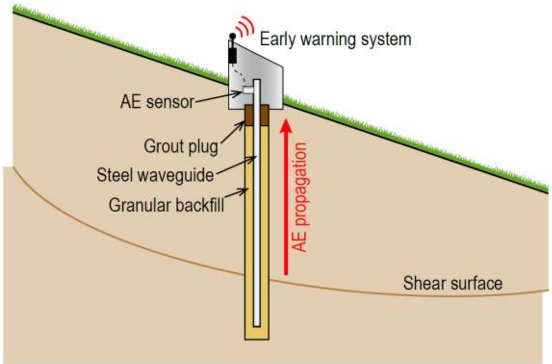

Figure 1: Illustration of the active waveguide system used for AE slope monitoring (modified after Smith 2015).

Fig. 1 shows an active waveguide system that is used for soil slope stability monitoring. The active waveguide is installed inside a borehole or driven into the soil, intersecting existing or anticipated shear surfaces, and comprises a steel tube with internal/external backfill, which is typically coarse-grained, 'noisy' soil (i.e. when deformed). As the slope moves, it causes deformations in the waveguide and backfill, which generates AE that propagate as guided waves up the steel waveguide to the sensor at ground level.

The AE measurement system is the only one in the world for soil slope monitoring with extensive validation and comprises: a 30 kHz resonant frequency transducer, coupled to the waveguide at the ground surface, to convert the AE into voltages; amplification and filtering to improve the signal-to-noise ratio (e.g. attenuate signals outside of 20-30kHz to remove environmental noise); and quantification of AE ring-down counts (RDC), which are the number of times the AE waveform crosses a pre-defined voltage threshold level in a pre-determined time interval and are a measure of signal energy.

In this paper, the development of strategies to extract knowledge on slope behaviour from AE measurements is detailed, which uses exemplar data from a field trial at Hollin Hill and large-scale laboratory experiments. Hollin Hill is a complex of interacting landslides situated 11 km to the west of Malton, North Yorkshire, UK. The landslides can be characterised as shallow rotational failures at the top of the slope that feed into larger scale slowly moving lobes of slumped material. Two of the lobes (shear surface depth between 1 and 2 m) were instrumented with three clusters of active waveguides (as described by Dixon et al. (2015)). Initially, empirical approaches for quantifying slope deformation behaviour from AE were established. Machine learning (ML) techniques for automated interpretation were subsequently developed. A conceptual framework for extracting knowledge from AE measurements for use in decision-making is presented.

2. Extracting knowledge on slope behaviour from AE

2.1 Relationship between AE and slope deformation behaviour

Koerner et al. (1981) proposed the following qualitative guide for interpretation of AE generated from deforming slopes: (a) no AE indicates stability; (b) moderate levels of AE indicate marginal stability; and (c) high levels of AE indicate that the slope is unstable. More recently, research has focused on the development of quantitative interpretation approaches: extensive field trials and large-scale laboratory experiments of AE slope monitoring have produced a significant body of evidence showing that generated AE rates are proportional to the rate of slope movement (Fig. 2) (Smith et al. 2014; Dixon et al. 2015; Smith et al. 2017; Dixon et al. 2018). Moreover, Smith et al. (2017) demonstrated that the AE approach can detect the development of new shear surfaces.

Dixon et al. (2015) introduced a coefficient of proportionality, C_p, as a function that defines the empirical relationship between AE rates generated from the active waveguide system in response to an applied velocity of slope movement:

$$AE_{rate} \propto \text{Velocity}, \quad \therefore\ AE_{rate} = C_p \times \text{Velocity}, \quad \text{where } C_p = f(\text{variables}) \tag{1}$$

The coefficient of proportionality is a measure of the system's sensitivity (i.e. the magnitude of AE rates produced in response to an applied velocity) and is dependent on many variables related to the AE measurement system such as: the sensor sensitivity controlled by signal amplification and voltage threshold; the depth to the shear surface that influences the magnitude of AE signal attenuation as it is transmitted from the shear zone to ground surface by the waveguide; and active waveguide properties such as the tube geometry and backfill properties. The magnitude of AE rate responses produced by each measurement system will depend on these factors, in addition to the rate of slope displacement.

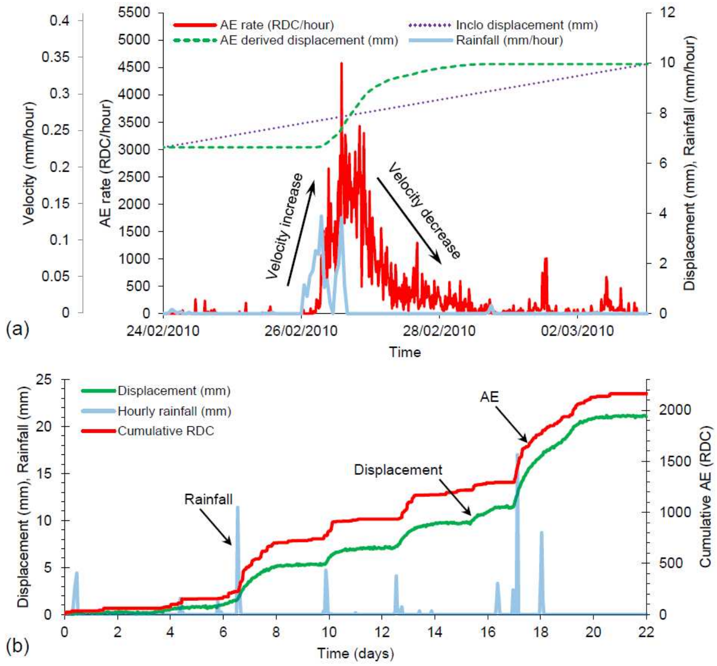

Figure 2: (a) AE rate, AE derived velocity, inclinometer-measured displacement, AE-derived displacement, and rainfall time series for a reactivated slope deformation event at Hollin Hill (modified after Dixon et al., 2015). (b) SAA-measured shear surface displacement, cumulative AE, and hourly rainfall versus time for a series of slide events at Hollin Hill (modified after Smith et al., 2014).

2.2 Back-calculating velocity of slope movement

Dixon et al. (2015) demonstrated how the coefficient of proportionality, if the AE rate-velocity relationship is assumed to be linear, can be back-calculated from slide events at Hollin Hill. AE rates are the time derivative of AE energy (i.e. cumulative RDC), and velocity is the time derivative of displacement. Therefore, using the shape of the AE rate–time profile, it was possible to determine a velocity-time profile for a slope movement event by equating the area under the AE rate-time curve to the magnitude of displacement measured by an adjacent inclinometer. The total event displacement was distributed proportionately to each trapezoidal integrand under the curve and the velocity over each trapezoid was determined using the displacement-time relation. Each point in time throughout the event subsequently had an AE rate and a corresponding velocity, and therefore a linear AE rate-velocity calibration could be determined. This allowed the velocity and cumulative displacement in subsequent slope deformation events to be quantified by applying the coefficient of proportionality to measured AE rates; an example is shown in Fig. 2(a). This method was shown to generate errors significantly less than an order of magnitude and is therefore consistent with standard classification for landslide movements.

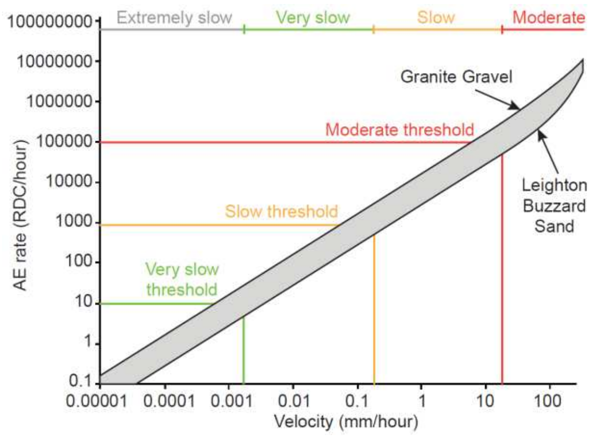

Figure 3: AE rate–velocity calibration relationships derived for a range of active waveguide backfills plotted on log scales with the standard landslide velocity scale superimposed, demonstrating that generic relationships can be obtained for groups of backfills to determine AE rate warning trigger levels based on slope displacement rates (modified after Smith et al., 2017).

2.3 Warning thresholds based on calibrated AE rate-slope velocity relationships

Fig. 3 shows how slope displacement rates can be quantified from measured AE rates to provide early warning of accelerating slope movements. A universal relationship for a range of active waveguide backfill materials is presented, which can be used to quantify changes in displacement rates. The measurements shown in Figure 3 were obtained from a series of large-scale slope failure simulations performed by Smith et al. (2017). The standard landslide velocity scale is superimposed to facilitate decision-making – for example, alerts are provided when slope movement progresses through 'very slow', 'slow' and 'moderate' thresholds. Accelerating trends whereby the slope progresses through successive velocity thresholds warn decision-makers of incipient failure.

2.4 Machine learning with classification

A study was conducted to develop and demonstrate the use of ML approaches to automatically classify landslide kinematics, based on the standard landslide velocity scale, using two AE features: AE rate and AE rate gradient (Deng et al. 2021a). AE rate gradient is the time derivative of AE rate and acceleration is the time derivative of velocity. Hence, AE rate gradient was used as an AE feature, in addition to AE rate, to interpret slope acceleration behaviour. Support Vector Machine (SVM), Random Forest (RF), and XGBoost were selected as three algorithms for automatic classification. The ML classification models were trained and tested using datasets from large-scale slope failure simulation experiments performed by Smith et al. (2017) and field measurements from the Hollin Hill landslide (Smith et al. 2014).

Fig. 4 shows AE data used for training (red circle, 70%) and testing (green star, 30%), and labels (obtained from SAA measurements) from large-scale slope failure experiments. The classifier was trained using the two AE features and the SAA-derived labels (Fig. 5). In testing, only the two AE features were input into the trained classifier, which predicted AE-derived labels, which were compared with SAA-derived target labels to assess the classification accuracy. The RF model performed best with a classification accuracy consistently greater than 90%. Fig. 5 shows the eight-label classification framework designed for the Hollin Hill site to incorporate velocity and acceleration behaviour (a_u is positive and a_l is negative). Fig. 6 shows measured AE rate and AE rate gradient with the SAA-derived labels from Hollin Hill during March to April 2016. An RF classifier was trained using 70% of the data, and the remaining 30% was used for testing.

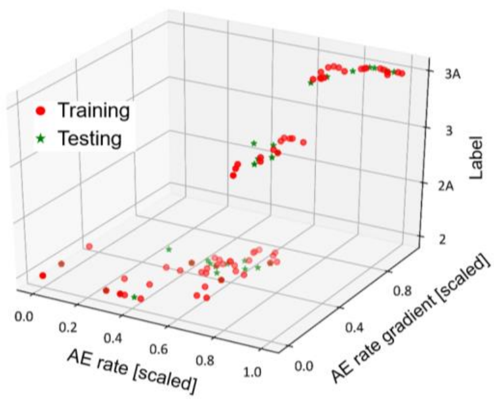

Figure 4: Training and testing datasets from large-scale slope failure simulation experiments: data points represent two AE features and corresponding SAA-derived labels (modified after Deng et al., 2021a).

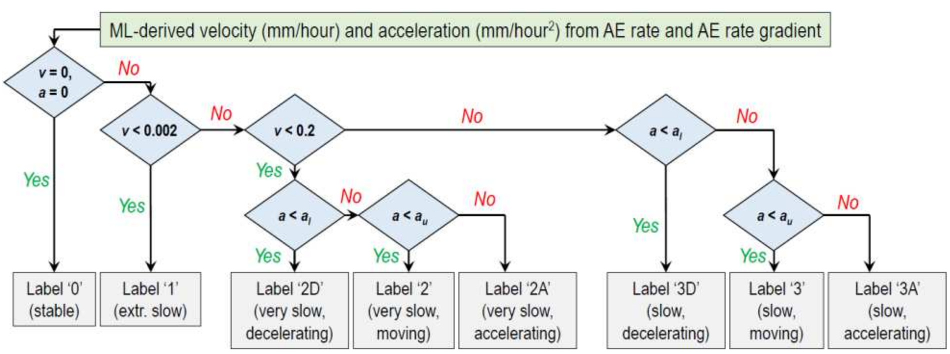

Figure 5: Flow diagram of slope behaviour classification for Hollin Hill field trial (modified after Deng et al., 2021a).

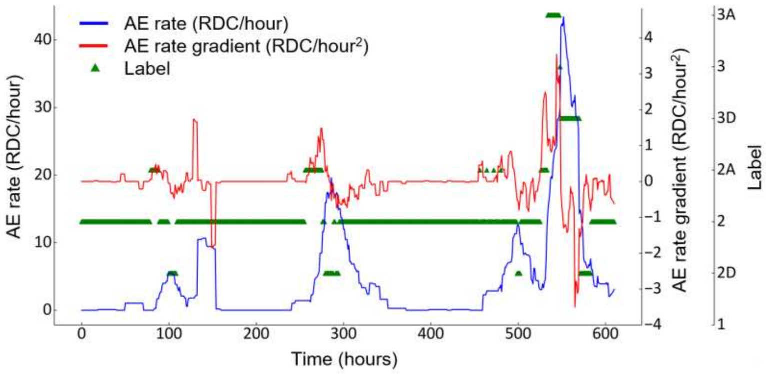

Figure 6: Time series from Hollin Hill: AE rate, AE rate gradient and SAA-derived target labels (modified after Deng et al., 2021a).

2.5 Machine learning with regression

Deng et al. (2021a) used ML classification techniques (Section 2.4) to develop a method to automatically identify landslide velocity scales and trigger warning levels based on AE measurements. This research was progressed by a study using ML regression techniques to automatically quantify absolute magnitudes of slope displacement from time series of AE and rainfall (Deng et al. 2021b). The regression ML approach was able to quantify slope displacement behaviour with a greater degree of accuracy than has been possible with previously established empirical approaches (Sections 2.2 and 2.3) (e.g. Smith et al. 2014, Dixon et al. 2015, Smith et al. 2017). AE, rainfall, and displacement measurements over a defined period from Hollin Hill were used for the multivariate regression in training. Subsequently, AE and rainfall measurements were input into the trained model to predict slope displacement. The slope displacement prediction performance of three ML regression models is compared in Fig. 7: Neural Network (NN), Extreme Learning Machine (ELM), and LASSO-ELM (LASSO is Least Absolute Shrinkage and Selection Operator). LASSO-ELM had the best match with the measured displacement relationship with time, and the greatest overall performance (e.g. Mean Absolute Percentage Error (MAPE) of 4%).

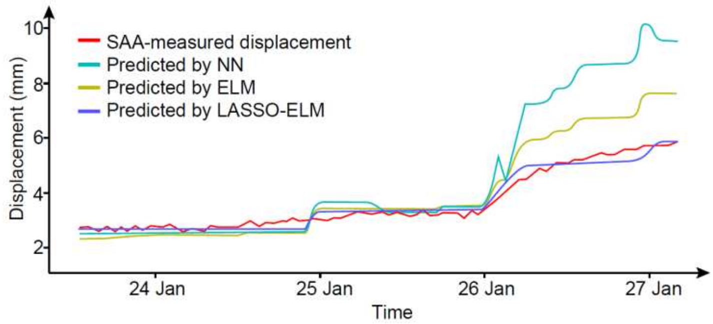

Figure 7: Displacement predictions using different ML techniques (modified after Deng et al., 2021b).

3. Discussion

Extensive field trials and large-scale laboratory experiments have shown that generated AE rates are proportional to the rate of slope movement. A coefficient of proportionality, C_p, was introduced as a function that defines the empirical relationship between AE rates generated from the active waveguide system in response to an applied velocity of slope movement. It was demonstrated how a velocity-time profile for a slope movement event could be derived by equating the area under the AE rate–time curve to the magnitude of displacement measured by an adjacent inclinometer, which allowed the velocity and cumulative displacement in subsequent slope deformation events to be quantified by applying the established coefficient of proportionality to measured AE rates (Dixon et al. 2015). A universal relationship for a range of active waveguide backfill materials was established from a programme of large-scale slope failure simulation experiments, which can be used to quantify changes in slope displacement rates (Smith et al. 2017). Machine learning (ML) approaches for automated interpretation were subsequently developed: classification of landslide kinematics, based on the standard landslide velocity scale, using two AE features (AE rate and AE rate gradient) (Deng et al. 2021a); and ML regression techniques to automatically quantify absolute magnitudes of slope displacement from time series of AE and rainfall (Deng et al. 2021b). Before this programme of research, AE interpretation was limited to qualitative frameworks (i.e. no AE indicating stability, high levels of AE indicating instability).

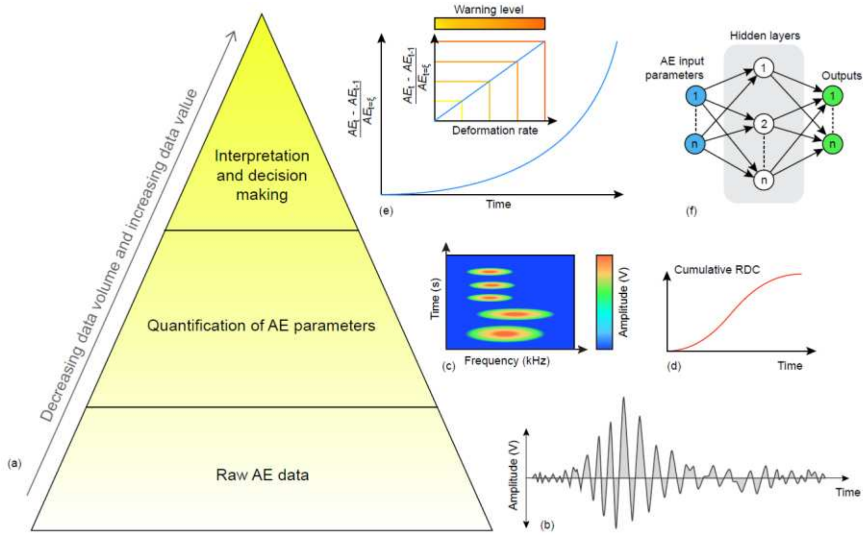

Figure 8: A conceptual framework for extracting information and knowledge from AE measurements for use in decision making: (a) progression from raw AE data to interpretation and decision making, (b) raw AE waveform, (c) joint time-frequency analysis, (d) cumulative RDC, (e) time series analysis for rates of change, and (f) artificial intelligence (modified after Smith & Dixon, 2020).

Informed by practice in smart infrastructure contexts, a conceptual framework for extracting information and knowledge from AE measurements for use in decision-making is presented in Fig. 8. Upward progression in the triangle decreases the volume of AE data and increases its value. AE parameters are quantified from the raw AE waveform data, and derived information is used as input into the interpretation and decision-making process. Interpretation and decision-making can use time series analysis to deliver information on rates of change (i.e. accelerating behaviour) or employ artificial intelligence algorithms, such as machine learning, trained to output slope behaviour information or alerts based on a suite of AE parameter inputs.

Selection of an AE interpretation strategy will be influenced by the operational context and could range from simplistic to complex. For example, Dixon et al. (2018) developed a low-cost AE landslide early warning system for use in vulnerable communities, which required a simple alert system that could trigger an audible and visual alarm to ensure robustness (i.e. minimise false alarms and also avoid telemetry issues in alert delivery) and reduce operating costs. To achieve this, a single threshold warning trigger was established based on a specific rate of slope movement. In contrast, a highly sophisticated smart infrastructure solution comprising real-time artificial intelligence could be appropriate for asset owners and operators managing significant infrastructure networks.

4. Summary

This paper has described a programme of research to develop strategies to extract knowledge on slope behaviour from AE measurements. Field trials and large-scale laboratory experiments have shown that generated AE rates are proportional to the rate of slope movement. A series of interpretation approaches were developed based on empirical relationships between AE rates and slope displacement rates, which can be used to quantify slope displacement rates from measured AE rates. Machine learning (ML) approaches for automated interpretation were subsequently developed: classification of landslide kinematics, based on the standard landslide velocity scale, using two AE features (AE rate and AE rate gradient); and ML regression techniques to automatically quantify absolute magnitudes of slope displacement from time series of AE and rainfall. Before this work, AE interpretation was limited to qualitative frameworks (i.e. no AE indicating stability, high levels of AE indicating instability). A conceptual framework for extracting knowledge from AE measurements for use in decision-making was presented. Selection of an AE interpretation strategy for a specific project could range from simplistic to complex and is influenced by the operational context (e.g. a low-cost landslide early warning system in vulnerable communities, or a real-time smart infrastructure system for asset owners/operators).

Acknowledgements

Alister Smith acknowledges the support of a UK Engineering and Physical Sciences Research Council Fellowship (Listening to Infrastructure, EP/P012493/1) and a Philip Leverhulme Prize in Engineering (PLP-2019-017). Lizheng Deng acknowledges the Tsinghua Scholarship for Overseas Graduate Studies (Contract Number: 2019273), which sponsored a visit to Loughborough University. Lizheng's research was supported by the Key Research and Development Program of Anhui Province (Grant No. 202104b11020021) and the open research program of Hefei Institute for Public Safety Research, Tsinghua University (Grant No. QHHFYKF202101).

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