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CLASSIFICATION OF SEISMIC PHASES BASED ON MACHINE LEARNING

Abstract. In the course of recent years, progresses in sensor innovation has lead to increments in the interest for automated strategies for investigating seismological signals. Fundamental to the comprehension of the components creating seismic signals is the information on the phases of seismic waves. Having the option to indicate the kind of wave prompts better performing seismic forecasting frameworks. In this article, we propose another strategy for the characterization of seismic waves quantification from a three-channel seismograms. The seismograms are isolated into covering time windows, where each time-window is mapped to a lot of multi-scale three-dimensional unitary vectors that portray the direction of the seismic wave present in the window at a few physical scales. The issue of arranging seismic waves gets one of ordering focuses on a few two-dimensional unit circles. We take care of this issue by utilizing kernel based machine learning that are remarkably adjusted to the geometry of the circle. The grouping of the seismic wave depends on our capacity to gain proficiency with the limits between sets of focuses on the circles related with the various kinds of seismic waves. At each signal scale, we characterize a thought of vulnerability connected to the order that considers the geometry of the dissemination of tests on the circle. At long last, we join the grouping results acquired at each scale into a unique label.

Key words: Seismology, machine learning, AI method, seismic waves, time window, three-channel seismograms, polarization content.

1 Introduction

Seismology is a field of study centered on expanding the comprehension of the Earth's internal structure through the investigation of Earth's inner changes through time. There is a solid correlation between seismology and the sound wave analysis [1-7]. A seismic wave is produced at a source, moves through a medium, and could be monitored by recording tools. Correspondingly, a sound wave is created by a source (for example a car signal), moves through the air, and could be heard by the human ear. The investigation of such signals can give data on the area of the source and the medium through which the wave has moved.

In the course of recent years, the examination of seismic signals has prompted a more profound comprehension of the development of our planet, permitted countries to investigate domains for underground regular assets, and given information valuable to alleviating the impacts of seismic earthquakes on the human populace [8-11]. The core interest of this development are techniques for examining seismic signals to obtain data valuable in relieving the impacts of earthquakes on society. These techniques may prompt advances in Early Seismic Warning Systems (ESWS) innovation and give an alternate point of view on the investigation of seismic waves. Specifically, we present a methodology for the classifying seismic phases utilizing AI methods.

2 Feature Extraction

Given the data set it may seem that it is advantageous to work with a changed adaptation of that information. In these cases, it is possible to consider measures taken from the information to be *features*. Features are helpful to cast the data from an alternate approach and guaranteeing that what is being studied is depicted by just its most appropriate segments. A single illustration of the benefit of extracting features from data originates from the investigation of musical genres. In the aforementioned case the processing file consists of fragments from melodic soundtracks coming from structure distinctive musical genres, for example, rock, traditional, electronic, hip-hop, and so on. The objective might be to take a melodic soundtrack for which the genre isn't known and decide in which kind it best "fits". Rather than working with the melodic time arrangement, it is more valuable to work with features that depict the track, for example, lumber, beat, recurrence substance, and zero intersections, to give some examples. By changing the information, it is at times more obvious structures in the information that lead to better characterization results.

Our examination of the seismogram is performed on a sliding time windows of the three- segment seismogram $[\mathbf{X}_E(t)\ \mathbf{X}_N(t)\ \mathbf{X}_Z(t)]^T$, t = 0, 1, ... (see Fig. 1). We structure the matrix **X** by gathering T tests of the seismogram and stacking them into a T × 3 grid

$$\mathbf{X} = \begin{bmatrix} X_E(t) & X_N(t) & X_Z(t) \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \mathbf{t=0,1,\ldots} \\ X_E(t+T-1) & X_N(t+T-1) X_Z(t+T-1) & \end{bmatrix} \quad (1)$$

It is important to understand however: the matrix **X** is actually a function of the time t at which we separate the time window. To mitigate the notations when there is no uncertainty, we decide not to make this reliance unequivocal. At the point when we think about two unique occasions t and t', or two distinct seismograms, we use subscripts to separate between the time windows, for example $\mathbf{X}_1$, $\mathbf{X}_2$. Overall, we use subscripts all through this proposal to demonstrate that the matching vectors, or networks, have been separated from various seismograms or at various occasions.

2.1 Geometric Polarization Analysis

In order to describe the polarization content in the time window **X** (1), we propose to break down the seismic waveform **X** into a number of components that describe the Earth movement at various scales. For each scale, we obtain the primary vector of the Earth movement at that scale and utilize this data as the classifier input. In this segment of the article, we show the multi-scale examination of the matrix **X**.

We decompose every one of the three sections of **X** with a l-level stationary wavelet transform (where $l \leq \log_2(T)$). The stationary wavelet decomposition is a redundant transform: we get l × T coefficients for every one of the three orientations of the seismogram. Luckily, there exists a quick algorithm to obtain the stationary wavelet decomposition: the "'a trou" calculation [26].

Figure 1 shows a seismic signal (upper left), its spectrogram (bottom left), and the stationary wavelet transform coefficients (right). The stationary wavelet transform can identify the second and third seismic waves, while the spectrogram scarcely changes when the waves show up (see Fig. 1-bottom left). Since seismograms can be estimated with extremely high accuracy utilizing few wavelet coefficients ([3, 16]), the wavelet transform is more qualified than a brief timeframe Fourier transform to identify seismic rushes of little plentifulness, as appeared in this model. Left: Z channel of a seismic signal (top) and spectrogram (bottom). The appearance times of three seismic waves are set apart by vertical bars. Note that the second and third waves scarcely cause any adjustments in the spectrogram. Right: stationary wavelet transform of the waveform given in left. The magnitude is color based and shown as a component of time, from fine scale (top) to coarse scale (bottom).

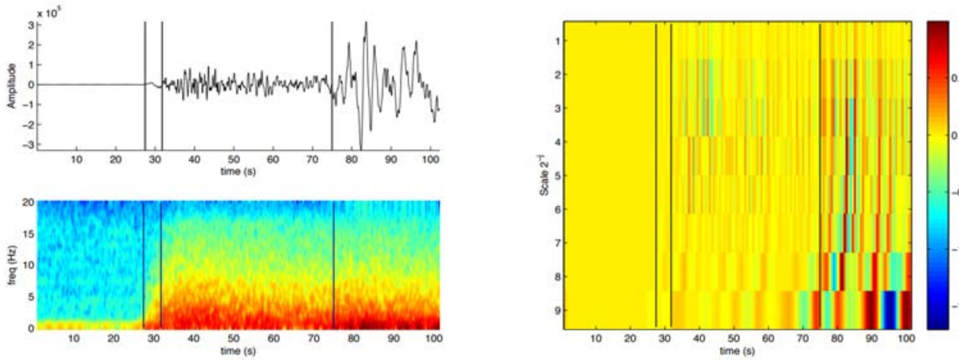

Figure 1 - A seismic signal

The result of the stationary wavelet examination of **X** at scale j can be shown as a T × 3 network W^j given by

$$\mathbf{W}^j = \begin{bmatrix} W_E^j(0) & W_N^j(0) & W_Z^j(0) \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ W_E^j(T-1) & W_N^j(T-1) & W_Z^j(T-1) \end{bmatrix} j = 1, \dots, l \qquad (2)$$

where every column is the stationary wavelet transform of the matching column in **X**. We pick l to be the most extreme scale permitted by the size of the signal (T) and the size of the channel. The matrix W^j encodes the movement of the Earth – estimated between time t and (t + T - 1) – in every one of the three orientations at scale j.

For the purposes of discovering the orientation related to the main energy at scale j, we process the singular value decomposition of W^j,

$$\mathbf{W}^j = \begin{bmatrix} \mathbf{U}^{j,1} & \mathbf{U}^{j,2} & \mathbf{U}^{j,3} \end{bmatrix} \begin{bmatrix} \sigma^{j,1} & 0 & 0 \\ 0 & \sigma^{j,2} & 0 \\ 0 & 0 & \sigma^{j,3} \end{bmatrix} \begin{bmatrix} [\mathbf{V}^{j,1}]^T \\ [\mathbf{V}^{j,2}]^T \\ [\mathbf{V}^{j,3}]^T \end{bmatrix} \qquad (3)$$

where $\sigma^{j,1} \geq \sigma^{j,2} \geq \sigma^{j,3}$, and $\| U^{j,i} \| = \| V^{j,i} \| = 1$, i = 1, 2, 3. Furthermore, the T-dimensional vectors $U^{j,1}$, $U^{j,2}$ and $U^{j,3}$ are orthogonal, and the 3-dimensional vectors $V^{j,1}$, $V^{j,2}$ and $V^{j,3}$ are also orthogonal. The vector $V^{j,1}$ is known as the polarization vector in the seismic literature. At each scale j, we only retain $V^{j,1}$ (and we discard all the remaining vectors), and we denote it by v^j,

$$\nu^j = \mathbf{V}^{j,1} \qquad (4)$$

We map the T × 3 network **X** to the 3 × l multiscale polarization lattice given by,

$$\mathbf{X} \mapsto [\nu^1 \quad \cdots \quad \cdots \quad \nu^l] \qquad (5)$$

This map obtains the orientation of maximal polarization over various frequency groups. Basically, it is a sifting of the polarization vectors over various regions in the recurrence range. The wavelet channel utilized is significant and based on the channel the nature of the polarization sifting will change. Wavelet filters that are orthogonal, and have linear phase, are assumed to perform better than non-orthogonal wavelets. Figure 2 shows feature extraction results. Left: stationary wavelet transforms for a few $\mathbf{X}_i$, i = 1, ... superimposed on each other; top two lines: scaling capacity (W^1), center two columns: coarsest (biggest scale) wavelet (W^2), bottom two lines: next better scale wavelet (W^3). Right: the vectors v^j_i are spoken to as focuses on the sphere; each column compares to a similar scale j as the two plots on the left (j = 1, 2, 3 start to finish). The shading and state of v^j encode the sort of wave: red star for P, blue cross for L, and green sphere for testing information.

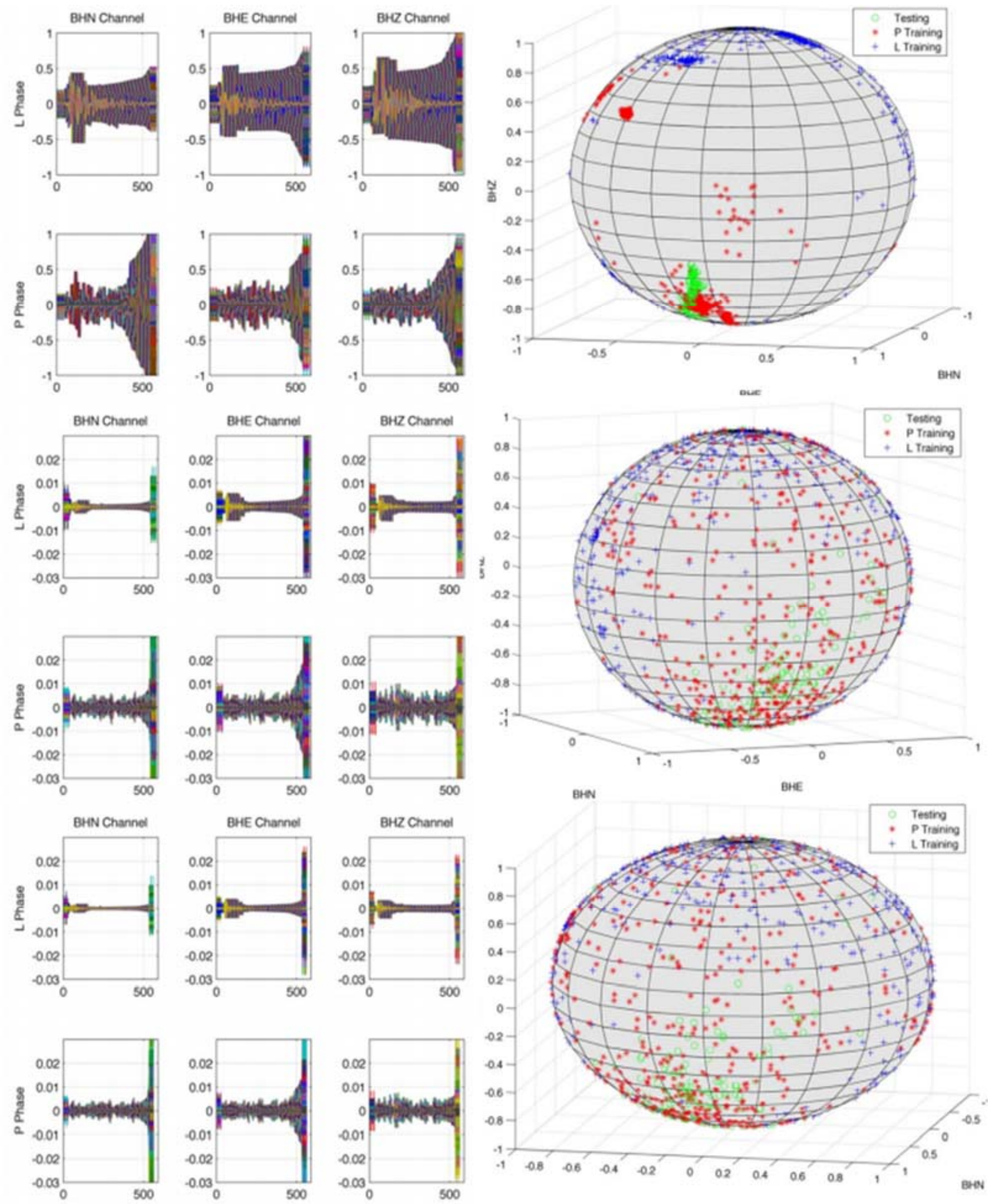

Figure 2 - Feature extraction results

2.2 Physical Interpretation

Each point of the sphere is tied to one-time window **X** over different levels of wavelet decomposition. This figure shows shading coded training and testing sets. The training set is made of marked stage classes, (blue-L stage and red-P stage), and the testing set is made of seismic windows of obscure stage.

Our first perception is that on every decomposition scale, points from comparable stage classes group close to one another and the concentration appears to decrease as the decay scale gets coarser. The grouping proposes possibility to characterize seismic waves as per a closeness to neighbors on the sphere. Figure 2 - Left shows a model where the plotted arrangement of testing focuses in green which are genuinely P-waves and watch they will in general bunch close to the P-wave preparing focuses.

The physical understanding of the polarization highlight vector is identified with the course of maximal signal energy and has been utilized to depict the orientation of predominant polarization in the seismology literature as mentioned before. For example, consider the following test. Assume you are blindfolded and need to find the position an individual who is conversing with you. At the point when that individual talks, you will in general turn toward the path where the sound is most grounded to give you a thought of where the individual is standing. Comparably, the polarization highlight vector gives comparable data about the seismic wave. The bearings implanted on the sphere S^2 comprise our element space.

3 Seismic Phase Learning

3.1 Supervised Learning

"Learning is defined as acquiring new or modifying existing knowledge, behaviors, skills, values, or preferences and may involve synthesizing different types of information" [26]. Deep learning endeavors to learn examples and regularities in data. A well known model is that of proposal matrices, which endeavor to give recommendations dependent on past encounters. For example, when clients give criticism, regarding different preferences of a tune, on web radio destinations, proposal matrices can take these contributions to recommend new melodies that might be engaging the client. The way toward obtaning data from the information gave and performing activities the data discovered sums up the premise of deep learning.

All the more explicitly, there is a class of deep learning undertakings that gains from information that has been completely marked. This is known as supervised deep learning, or managed learning. This approach will be the focal point of this part and will be introduced from the viewpoint of learning the period of an unlabeled seismic wave.

3.2 Classifiers

We expect that our preparation set is made out of N time windows $\mathbf{X}_i$, i = 1, ..., N. From every $\mathbf{X}_i$, we figure the l solitary vectors $v^1{}_i,..,v^l{}_i$. We will develop at each scale j a capacity f^j that maps a testing point v^j, with an obscure name, from the sphere S^2 to the span [-1, 1],

$$f^j: v^j \in \mathcal{S}^2 \mapsto f^j(v^j) \in [-1,1]$$

We assessed three distinctive arrangement strategies (three unique sorts of fj) utilizing the part depicted in segment 3.3.1: kernel ridge regression, kernel support vector machines, and k-nearest neighbors. We utilize a similar sort of characterization strategy fj for all the scales j = 1, ..., l. Just the parameters of each capacity fj differ over the scales. Further on, we depict the three distinct methodologies. Extra insights concerning the executions of these methods can be found in ([12,13] and references in that).

3.3 Learning on the Sphere

Figure 2-left shows the yield of the stationary wavelet transform (plotted on each other) for a few time windows $\mathbf{X}_i$ removed from various seismograms [14-18]. The main two columns show the scaling capacity coefficients ($\mathbf{W}^1$) for the L and P waves, separately. The subsequent two lines show the coarsest (biggest scale) wavelet coefficients ($\mathbf{W}^2$), and the third two columns show the following smaller scale wavelet coefficients ($\mathbf{W}^3$). Figure 2-right shows the area of each $v^j{}_i$ related with the time window $\mathbf{X}_i$. The shading and state of the spot speaking to $v^j{}_i$ on the sphere encodes the kind of wave: red star for P, blue cross for L. The green spheres demonstrate the area of testing information for which we don't have the foggiest idea about the kind of wave [19-23]. The green spheres should be named red stars (P waves) or blue crosses (L waves). Notwithstanding the way that the $\mathbf{X}_i$ are obtained from various seismograms estimated at various stations, the $v^j{}_i$ normally bunch together (see for example $v^1{}_j$ in the top line of Figure 2-right). We likewise see that the homogeneity of the conveyance of the $v^j{}_i$ shifts as an element of the scale j, demonstrating that a few scales will be more helpful than others to arrange the time windows $\mathbf{X}_i$.

The genuine trouble here is that the standard Euclidean separation between two vectors $v^j{}_1$ and $v^j{}_2$, beginning from two distinctive time windows $\mathbf{X}_1$ and $\mathbf{X}_2$, is insubstantial in this specific circumstance. For the situation where focuses are inspected from a surface, or all the more for the most part a complex, we have to gauge separations utilizing the geodesic separation characterized on the complex. Then again, we can build an implanting of the complex into R^m that ideally saves separations (for example bi-Lipschitz), and measure separates in R^m.

For our situation, we approach a shut structure articulation for the geodesic separation and are in this way ready to represent the nonlinear structure of the element space to arrange the vectors $v^j{}_i$. We note that when the genuine geodesic separation isn't open, an estimate to the geodesic separation is generally near ideal. For example, Turaga et al. (2008) indicated that the Procrustes approximations to the geodesic separation on the Stiefel and Grassmann manifolds yield results that are near ideal for different issues including the estimation of model parameters in dynamic matrix, movement acknowledgment, and video-based face acknowledgment [25]. In any case, the calculation of the geodesic separation may end up being over the top expensive. Sommer et al. (2010) indicated that the addition in precision accomplished with the genuine geodesic didn't exceed the calculation cost when the specific geodesic was contrasted with a direct estimation with regards to Principal Geodesic Analysis [24, 27-31].

3.4 Phase Classification on the Sphere

The grouping of a period window **X** depends on a preparation set of named information to in part populate the spheres, at all scales j = 1, ..., l, with data about the kind of waves at the relating areas on the spheres (see figure 2-right). We join the data given by the preparation marks with the information about the geometry of the sphere to become familiar with a capacity that depicts the limit between P-waves and L-waves. In this work, we assessed three distinctive regulated learning strategies to group the vectors v^j_i: portion edge relapse, part bolster vector machines, and k-closest neighbors. The key part is the meaning of a measurement and its related portion to evaluate vicinity on the sphere to in the end consolidate the characterization results at all scales to produce a mark.

In the accompanying sub-segments, we depict the order of the vector v_j at a given scale j. We at that point propose a data hypothetical measure to consolidate mono-scale characterization scores into a last grouping outcome.

4. Results

4.1 Evaluation Strategy

As a seismic tremor arrives at the RMSN, it is recorded put away for future examination. Over the system, a seismic tremor might be able to be detected at one station yet not at another. For example, a sensor at a chronicle station might be down for fixes which in this way, comprises a botched account chance.

In the regulated learning worldview, one must ensure a particular classifier isn't prepared with information that will be utilized for testing the given classifier. At the point when information is constrained, one must think about elective methodologies in surveying the viability of a calculation. In these cases, we utilize the strategies for cross-approval to assess the exhibition of the learning methods. These procedures ordinarily save a part of the general information for preparing and afterward utilize the rest of the information for testing. The segments held for testing and preparing are rotated, bringing about a n-overlap cross-approval, where n is the occasions the classifier is tried and prepared.

For the arrangement of seismic stages, we utilized a cross-approval technique that utilizes seismic information gathered over the full system. In an arrangement run, we are utilizing a subset of the informational collection, where each recording station in the system was utilized in gathering the information. The main imperative for a given run is that information from a seismic tremor isn't gathered at various chronicle stations in the system. In a characterization run, we work with 10 unmistakable seismic tremors estimated some place in the system. During cross-approval, we forget about one tremor seismogram and utilize the staying 9 seismograms to prepare our classifier. For instance, if we somehow managed to have a similar tremor show up twice at various detecting stations in our system, this grouping would be considered as cheating in light of the fact that a quake radiating from some source estimated at two unique stations will vary just by a direct change. The straight change would be incited on the signal because of the nearby geography of the account station. An elective methodology for cross-approval is use information just gathered at a given station. In spite of the fact that this would be a legitimate methodology, it isn't attainable in our examination because of information amount restrictions

4.2 Comparison of approaches

Table 1 shows test results under the methodology proposed by Jackson et al. (1991). It shows the level of time windows for which the speculation H_0, "X contains a P wave" was acknowledged as a component of the test edge η. These outcomes relate to our execution of the calculation of [15] on our dataset. At the point when the edge $\eta = 0.30$, the Lg are mistakenly characterized 33.25% of the time and thusly are effectively ordered 66.75% of the time. This is a sensible location level of the Lg waves. Sadly, a similar estimation of the edge for the invalid hypothesis was just acknowledged 23.62% and 44.56% of the ideal opportunity for the Pg and Pn waves, individually. By dismissing the invalid speculation, the classifier misses the P waves practically constantly, in this way yielding poor order of Pn and Pg waves.

Diminishing η surely helps the recognition of the P waves, yet comes at the cost of noteworthy misclassifications of the Lg waves in that the invalid speculation is acknowledged when it ought not be. In any case, our methodology had the option to identify with a similar precision both P and L waves.

Detection of the P and L waves using a hypothesis test.

η	Pr(H0|Lg) > η	Pr(H0|Pg) > η	Pr(H0|Pn) > η
0.50	0.00	0.00	0.00
0.40	12.29	8.11	20.46
0.30	33.25	23.62	44.56
0.20	54.24	44.43	64.89
0.10	70.09	66.51	86.88
0.05	76.09	75.98	93.31

5 Conclusion

Our objective in this work was to investigate the utilization of AI as it applies to seismology. Specifically, we found a change that takes windows of three-channel seismic information and implants them on the unit circle over various recurrence scales with the end goal that the area of the installing portrays the seismic stage content in the wave. The utility of this change is focused on the stage grouping in the component space. Basically, windows of seismic information relating to the equivalent seismic stage class will in general be genuinely situated close to one another in the element space. Having this kind of structure over the component space at various degrees of sign goals gives a solid establishment to the use of regulated learning methods for stage grouping. Furthermore, the basic geometric structure of the component space takes into account administered learning strategies to be made an interpretation of straightforwardly to the element space. Fundamentally, we have told the best way to "lift" learning strategies to a non-straight complex.

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МАШИНАЛЫҚ ОҚЫТУ НЕГІЗІНДЕГІ СЕЙСМИКАЛЫҚ ФАЗАЛАР КЛАССИФИКАЦИЯСЫ

Аннотация. Соңғы бірнеше жыл ішінде сенсорлық технологияның дамуы сейсмологиялық сигналдарды талдауға арналған компьютерлік әдістерге сұранысты арттырды. Сейсмикалық сигналдарды тудыратын механизмдерді түсінудің негізі – сейсмикалық толқындар фазасын жан-жақты білу мәнін білдіреді. Толқын түрін анықтау мүмкіндігі сейсмикалық ертерек ескерту жүйесінің жақсы жұмыс істеуіне септігін тигізеді.

Бұл жұмыста үшарналы сейсмограммамен өлшенген сейсмикалық толқындарды жіктеудің жаңа әдісін ұсынамыз. Сейсмограммалар бір-бірімен қиылысатын уақытша терезелерге бөлінген. Мұнда уақытша әр терезе бірнеше физикалық масштабтағы терезеде орналасқан сейсмикалық толқын бағытын сипаттайтын көп масштабты, үшөлшемді унитарлық векторлар жиынтығымен көрсетіледі. Сейсмикалық толқындарды жіктеу міндеті екіөлшемді бірлік сфералары бойынша жіктеу нүктелерінің біріне айналады. Біз бұл есепті сфера геометриясына бейімделген машиналық оқыту әдістерін қолдану арқылы шешеміз. Сейсмикалық толқынның жіктелуі түрлі сейсмикалық толқындарға байланысты сфералардағы нүктелер жиынтығы арасындағы шекараны зерттеу қабілетіне негізделген. Әр сигнал шкаласында біз классификацияға қолданылатын белгісіздік ұғымын анықтаймыз, ол сфера бойынша үлгінің таралу геометриясын ескереді. Соңында әр шкала бойынша алынған жіктеу нәтижелерін ерекше белгіге біріктіреміз.

Сейсмология – уақыт өте келе жердегі ішкі өзгерістерді зерттеу арқылы жердің ішкі құрылымы туралы түсініктерді кеңейтуге бағытталған зерттеу саласы. Сейсмология мен дыбыстық толқындарды талдау арасында тығыз байланыс бар. Сейсмикалық толқын шығу көзінде пайда болады да, орта арқылы өтіп, оны

жазба құралдарымен басқаруға болады. Тиісінше дыбыстық толқын шығу көзі арқылы жасалады (мысалы, автомобиль сигналы), ауа арқылы қозғалады да, адам құлағына естіледі. Мұндай сигналдарды зерттеу көздің ауданы мен толқын өткен орта туралы мәліметтер бере алады.

Соңғы жылдары сейсмикалық сигналдарды зерттеу планетамыздың дамуын тереңірек түсінуге әкелді. Көптеген елдерге жерасты тұрақты активтері бар аймақтарды зерттеуге мүмкіндік берді және сейсмикалық жер сілкіністерінің адам санына әсерін азайту үшін құнды ақпарат берді. Бұл дамудың басты қызығушылығы – жер сілкінісінің қоғамға әсерін азайту мен құнды мәліметтер алу үшін сейсмикалық сигналдарды зерттеу әдістері болып саналады. Бұл әдістер ерте сейсмикалық ескерту жүйесінің (ESWS) инновациясындағы прогресті ынталандырады және сейсмикалық толқындарды зерттеудің балама перспективасын ұсынады. Атап айтқанда, AI әдістерін қолдану арқыл сейсмикалық фазаларды жіктеудің әдістемесін ұсынамыз.

Жұмыстағы мақсатымыз – AI әдістерін сейсмологияда қолдануды зерттеу. Атап айтқанда, үшарналы сейсмикалық ақпарат терезелерін алатын және түпкілікті мақсаты бар түрлі қайталану ауқымында оларды бір шеңберге орналастыратын өзгерісті таптық, осылайша орнату аймағы сейсмикалық кезеңнің мазмұнын толқынмен көрсетеді. Бұл өзгерістің тиімділігі компоненттер кеңістігіндегі кезеңдерді топтауға бағытталған. Жалпы алғанда, сейсмикалық кезеңдердің эквиваленттік класына қатысты сейсмикалық ақпарат терезелері, жалпы жағдайда, элементтер кеңістігінде бір-біріне жақын орналасады. Әртүрлі деңгейдегі символдық мақсаты бар компоненттер кеңістігінде осындай құрылымның болуы топтық кезең үшін оқытудың реттелетін әдістерін қолдануға сенімді негіз береді. Сонымен қатар, компоненттік кеңістіктің негізгі геометриялық құрылымы элементтер кеңістігіне тікелей түсіндірілуі тиіс басшылыққа алынған оқыту стратегияларын ескереді. Шындығында біз оқыту стратегиясын кешенді түрде қалай «көтеру» керектігі туралы баяндадық.

Түйін сөздер: сейсмология, машиналық оқыту, AI әдісі, сейсмикалық толқындар, уақытша терезе, үшарналы сейсмограммалар, поляризация мазмұны.

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КЛАССИФИКАЦИЯ СЕЙСМИЧЕСКИХ ФАЗ НА ОСНОВЕ МАШИННОГО ОБУЧЕНИЯ

Аннотация. За последние несколько лет достижения в области сенсорных технологий привели к увеличению спроса на компьютеризированные методы анализа сейсмологических сигналов. Центральным в понимании механизмов, генерирующих сейсмические сигналы, является знание фаз сейсмических волн. Возможность указать тип волны приводит к лучшему функционированию сейсмических систем раннего предупреждения.

В данной работе мы предлагаем новый метод классификации сейсмических волн, измеренных по трехканальным сейсмограммам. Сейсмограммы разделены на перекрывающиеся временные окна, где каждое временное окно отображается на набор многомасштабных трехмерных унитарных векторов, которые описывают ориентацию сейсмической волны, присутствующей в окне, в нескольких физических масштабах. Задача классификации сейсмических волн становится одной из точек классификации на нескольких двумерных единичных сферах. Мы решаем эту проблему, используя методы машинного обучения, которые адаптированы к геометрии сферы. Классификация сейсмических волн основана на нашей способности изучать границы между наборами точек на сферах, связанных с различными типами сейсмических волн. На каждой шкале сигнала мы определяем понятие неопределенности, приложенное к классификации, которая учитывает геометрию распределения выборок на сфере. Наконец, мы объединяем результаты классификации, полученные в каждой шкале, в уникальный ярлык.

Сейсмология – эта область исследований, сосредоточенная на расширении понимания внутренней структуры Земли путем исследования внутренних изменений Земли во времени. Существует тесная связь между сейсмологией и анализом звуковых волн. Сейсмическая волна генерируется у источника, проходит через среду и может контролироваться записывающими инструментами. Соответственно, звуковая волна создается источником (например, автомобильным сигналом), движется по воздуху и может быть услышана человеческим ухом. Исследование таких сигналов может дать данные о площади источника и среды, через которую прошла волна.

В течение последних лет изучение сейсмических сигналов привело к более глубокому пониманию развития нашей планеты, позволило странам исследовать области для подземных регулярных активов и предоставило информацию, ценную для смягчения воздействия сейсмических землетрясений на человеческое население. Основным интересом этой разработки являются методы изучения сейсмических сигналов для получения данных, ценных для уменьшения воздействия землетрясений на общество. Эти методы могут стимулировать прогресс в инновациях систем раннего сейсмического оповещения (ESWS) и давать альтернативную точку зрения на исследование сейсмических волн. В частности, мы представляем методологию классификации сейсмических фаз с использованием методов AI.

Наша цель в этой работе состояла в том, чтобы исследовать использование метода AI применительно к сейсмологии. В частности, мы нашли изменение, которое берет окна трехканальной сейсмической информации и имплантирует их в единичный круг по различным шкалам повторения с конечной целью, чтобы область установки отображала содержание сейсмической ступени в волне. Полезность этого изменения сфокусирована на группировке этапов в пространстве компонентов. В основном, окна сейсмической информации, относящиеся к эквивалентному классу сейсмических стадий, в общем случае будут действительно расположены близко друг к другу в пространстве элементов. Наличие такого рода структуры в пространстве компонентов с различными уровнями знаковых целей дает прочное основание для использования регулируемых методов обучения для групповой стадии. Кроме того, базовая геометрическая структура пространства компонентов учитывает управляемые стратегии обучения, которые должны быть прямо интерпретированы для пространства элементов. По сути, мы рассказали, как лучше всего «поднять» стратегии обучения в сложный комплекс.

Ключевые слова: сейсмология, машинное обучение, метод AI, сейсмические волны, временное окно, трехканальные сейсмограммы, поляризационное содержание.

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