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Estimation of Rock Joint Trace Length Using a Support Vector Machine (SVM)

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Abstract

Jointed rock mass modeling needs the geometrical parameters of joints such as orientation, spacing, trace length, shape, and location. The rock joint trace length is one of the most critical design parameters in rock engineering and geotechnics. It controls the stability of the rock slope and tunnels in jointed rock masses by affecting the rock mass strength. This parameter is usually determined through a joint survey in the field. Among the parameters, trace length is challenging because a complete joint plane within a rock mass cannot be observed directly. The development of predictive models to determine rock joint length seem to be essential in rock engineering. This research made an effort to introduce a support vector machine (SVM) model to estimate rock joint trace length. The SVM is an advanced intelligence method used to solve the problem characterized by a small sample, non-linearity, and high dimension with a good generalization performance. In this study, three data sets from the sedimentary, igneous, and metamorphic rocks were organized, with the location of joints on the scanline, aperture, spacing, orientation (D/DD), roughness, Schmidt rebound of the joint's wall, type of termination, trace lengths in both sides of the scanline and joint sets were measured. The results of SVM prediction demonstrate that predicted and measured results are in good agreement. The SVM model-based results were compared with those obtained from field surveys. The proposed SVM model-based model was very efficient in predicting rock joint trace length values. The actual trace length could be estimated; thus, the expensive, difficult, time-consuming, and destructive joint surveys related to obscured joints could be avoided.

Keywords:
rock exposure; joint trace length; scanline sampling; support vector machine

1. Introduction

Discontinuities of rock masses make rock mechanics a unique topic (**Hudson and Harrison, 1997**). The characteristics of discontinuities and intact rocks control the engineering properties of rock masses. To predict the behaviour of related structures to rock masses, characterizing the discontinuity geometry and the geomechanical properties of the discontinuities and the intact rock is necessary. Discontinuities are weak planes with zero or low tensile strength (**Palmstrom, 1995**). Joints are discontinuities with no noticeable movement (**Hudson and Harrison, 1997**), which originate in all rock types in about 1km of the Earth's surface, at all orientations and sizes ranging from a few millimeters to several hundred meters. Certain joints are related to relatively simple mechanisms, such as the columnar jointing formed by stresses induced during the cooling of basalts and the slabbing joints caused by diurnal temperature changes on exposed rock faces (**Priest, 1993**). **Price** (**1966**), stated that joints in horizontally bedded rocks might be generated by stress changes induced by geological uplift. Also, **Palmstrom** (**1995**) noted that some types of joints perhaps developed due to the unloading of the rock mass when the cover is eroded, discontinuities established as a product of exfoliation, along the foliation planes in metamorphic rocks and along the bedding planes in sedimentary rocks. Rock joints affect the rock mass strength directly or indirectly (**Gumede and Stacey, 2007**). Since some researchers addressed changes in spacing, trace length, and appearance of rock mass joints as weathering progresses (**Karpuz and Pasamehmetoglu, 1997; Judy, 2002; Gurocak and Kilic, 2005; Park and West, 2005**). **Palmstrom** (**1995**) stated that the trace length of rock joints is related to the aperture, shape, and size of joints. Also, they are primarily related to rock types, size, and geometry of the rock mass.

The length of the possible failure plane and the size blocks are described by the joint trace length (**Gumede and Stacey, 2007; Sari, 2009**). The stability of tunnels in rock masses at a low depth is principally affected by the stability of rock blocks. Even though the geometrical parameters of joints, particularly its trace length, strong-

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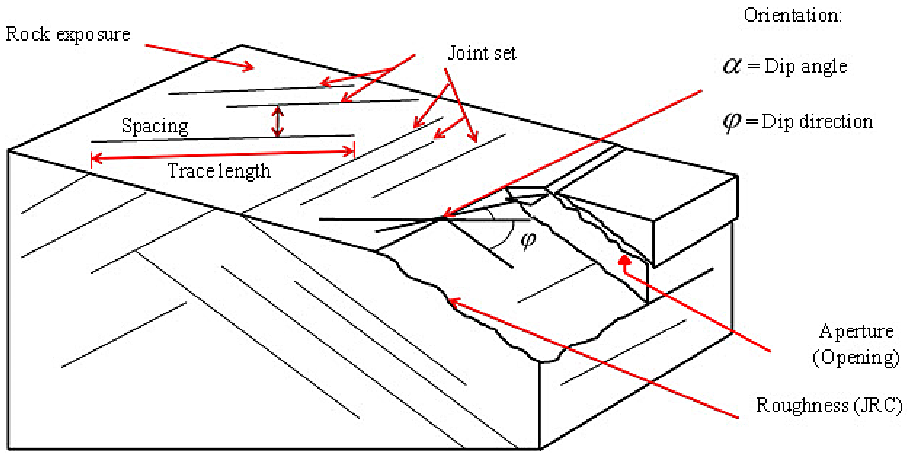

Figure 1: Illustration of joint properties in rock masses (Adopted from (Wyllie, 1999))

ly affect the fluid-mechanical behaviour of rock masses and control rock mass strength, rock slope, and underground space stability (**Meyer and Einstein, 2002; Odling, et al., 1999**). Consequently, joint geometry parameters must be measured precisely. Since rock exposures are small and 2D, joint trace length can be approximately measured only by observing the discontinuity trace length on a rock surface. Eventually, the joint trace length is one of the most challenging properties to measure precisely (**Einestein et al., 1983; Brown, 1981; Priest, 1993; Brown, 1981; Villaescusa and Brown, 1992**).

The new technique for estimating joint trace length is derived by using the support vector machine (SVM). Recently, new techniques, such as artificial intelligence (e.g. SVM, Artificial Neural Network (ANN)), Genetic Algorithm (GA), and Fuzzy Logic (FL) have been applied in the prediction and optimization in the field of geotechnical engineering. For example, **Goh** (**1994**) used ANN to evaluate the liquefaction potential of soil (**Goh, 1995b; Goh, 1995c; Goh, 1996; Chan et al., 1995; Teh, et al., 1997; Lee & Lee, 1996; Abu-kiefa, 1998**) used an artificial neural network to predict the load capacity of piles. SVM is a statistical learning theory that has been developed in the reverse order to the development of neural networks. Also, it is an excellent kernel-based tool for binary data classification and regression (**Burges, 1998; Vapnik, 1995; Vapnik, 1998**). This system can generalize a solution from the pattern presented during the training process. Predictions can be made based on previous learning when the network is trained with enough sample datasets. Increasing the applications of SVM in the field of geotechnics, geology, and rock mechanics has been observed (**Amini et al., 2012; Zadhesh et al., 2014; Tiryaki, 2008; Ali & Chawathe, 2000; Wyllie, 1999; Zhang et al., 2009; Chengxiang, et al., 2017; Xi, et al., 2021; Vassilios and Konstantinos, 2021; Danial Jahed, et al., 2020; Abiodun Ismail and Sangki, 2021; Zheng, et al., 2020**). These studies reveal that SVM is efficient in solving problems in geosciences. Ultimately, this research has made an effort to introduce an SVM model to estimate the rock joint trace length using the joint properties, which can be measured precisely.

2. Parameters of Rock Joints

Since the primary purpose of this paper is to estimate one of the geometrical characteristics of the rock joint, it is better to explain some of the properties briefly. **Figure 1** illustrates the parameters which are measured in the joint survey.

- The intensity of joints (the number of joints per unit distance normal to the orientation of the set) in a rock mass is stated as ***joint spacing,*** and it is taken as the perpendicular distance between adjacent joints (**Price, 1966**). This paper used intersection distance (length along the scanline to the intersection point with the joint) to describe joint spacing.
- The perpendicular distance separating adjacent rock walls of an open joint is called the ***joint aperture*** in which the **intervening** space is filled with air or water (**Villaescusa and Brown, 1992**). The apertures of natural discontinuities are likely to vary widely over the extent of the joint (**Barton, 1983**).
- Determining the space position of the joint plane in space is called **joint orientation**, which defines the dip and dip's direction.
- Irregularities of joint surface can be described as ***joint roughness*** and can be stated in Barton's Joint **roughness** coefficient (JRC). The value of JRC can be estimated by visually comparing the joint surface condition with standard profiles (**Priest, 1993**).
- Two matching surfaces of rock joints in the 3D space are called ***joint walls***. The joint walls' condition is a main joint **characteristic** that reflects its weathering process. Thus, we used the Schmidt rebound number to represent this effect in the joint walls.
- The distance from the intersection point on the scanline to the end of the joint trace is mentioned as ***joint trace length***. There will be two semi-trace lengths associated with each discontinuity located on the right and the left of a scanline. It can be help-

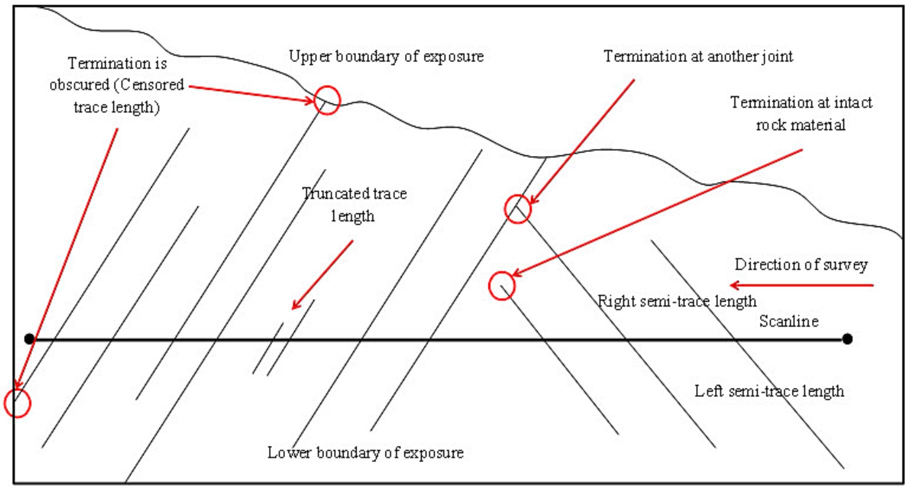

Figure 2: Schematic view of scanline sampling and type of joint termination

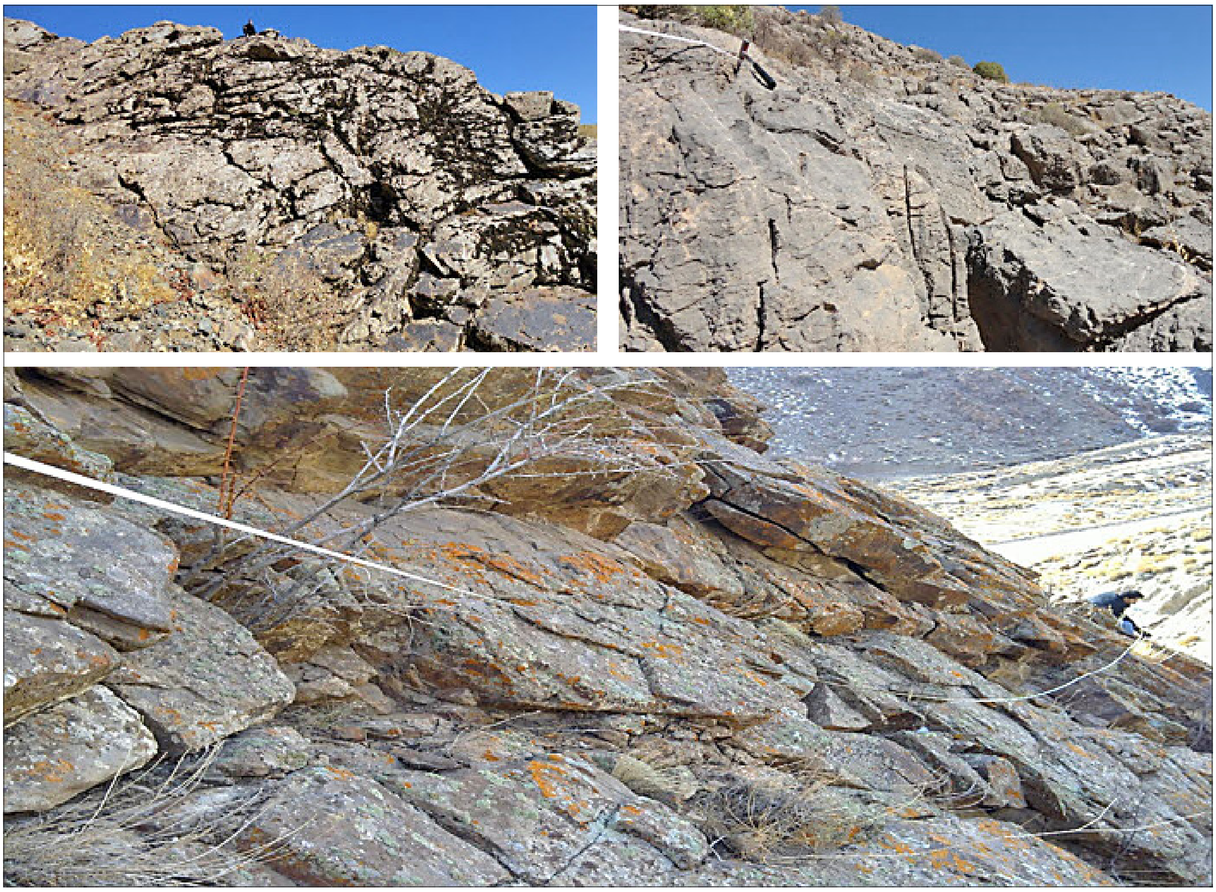

Figure 3: Views of rock exposures: (a) Sarshiw andesite, (b) Sarshiw metamorphic, and (c) Sedimentary rock of the Tazare coal mine

ful to keep a record of the nature of the termination of each semi-trace. 1: joint trace terminates in intact rock, 2: terminates at another joint, 3: termination is obscured. A joint trace length can be covered by blocks rock, scree, soil, vegetation, or extending beyond the exposure limits (**Priest, 1993**).

- A **joint set** consists of parallel or sub-parallel joints and the number of sets that characterize a particular rock mass geometry.

3. Data Collection

Measuring joint parameters is a vitally important task in rock engineering because these properties strongly influence rock masses' mechanical and geometrical behaviour (**Baecher, 1983**). The success of discontinuity analysis greatly depends on how correctly in situ joints are surveyed and modeled for the study (**Song, 2006**). By using scanline-sampling or window-sampling, size parameters of joints are collected, which record only the exposed surfaces; therefore, they cannot be used in defining the 3D nature of joints. In the scanline sampling method, less geological mapping knowledge is required. However, in window mapping, more data are collected over larger areas (**Menachem, 2008; Gumede and Stacey, 2007**). Obtained data in this research are contained in the scanline mapping method with which all properties of those joints that intersect a scanline are recorded. In **Figure 2**, a schematic view of the scanline sampling is shown.

Truncations and censoring are sampling biases that represent the inability to record joints smaller than the detection limits and those affected by exposure conditions, respectively (**Hudson and Priest, 1983; Priest and Hudson, 1976; Priest and Hudson, 1981; Einstein et al., 1983**).

The qualities and quantities of measured data of geometric properties obtained from field mapping on outcrops of limited areas and borehole logging of limited borehole diameters and depths contain a significant degree of uncertainty. To represent more realistic fracture networks, an approximately planar rock face that is clean and large relative to the size and spacing of exposed joints must be selected. Which selected site should contain 150 to 350 joints and approximately 50% of which should have at least one termination visible (**Priest, 1993**).

For the purpose of research, the exposure of Sarshiw andesites located 40km from Marivan City in the Kurdistan Province, west of Iran for igneous and metamorphic rocks, and the Tazare coal mine located 70km from Shahrood City in the Semnan Province, north-east of Iran for sedimentary rocks were selected. In **Figure 3,** three views of studied sites of all surveyed rock types are shown.

4. Support vector machine (SVM)

The support vector machine (SVM) is an excellent kernel-based tool for binary data classification and regression, presented by **Vapnik (1995)** and **Vapnik (1998)**. The method transforms the importable space into a high-dimensional space through a nonlinear transformation defined by an inner product function. Also, the theoretical foundation of this system is based on the minimization of structural risk. It is better than the routine Neural Network based on the traditional minimization principle of experience risk. A nonlinear relationship between the input and output variables in the high-dimensional space is found in the SVM algorithm. SVM arithmetic takes the form of a problem in convex quadratic optimization, ensuring that the solution is optimal. The method resolves practical issues like small samples, nonlinearity, and high-dimensional input spaces. The degree of a problem's complexity does not depend on the dimension of the characteristic equations being optimized, which SVM has an excellent capability to generalize (**Liu et al., 2008**).

To generalize the SVM algorithm for regression analysis, an analog of the margin is created in the space of the target values (y) by sub-element's ε-insensitive loss function (**Shojai et al., 2009; Vapnik, 1999; Gunn, 1998**).

$$\left|y-f(x)\right|_{\epsilon}=\max\left\{0,\left|y-f(x)\right|-\varepsilon\right\} \tag{1}$$

To estimate a linear regression:

$$f(x)=(w.x)+b \tag{2}$$

With precision, one minimizes:

$$\frac{1}{2}\|w\|^2+C\sum_{i=1}^{m}\left|y-f(x)\right|_{\varepsilon} \tag{3}$$

The optimization objective of the standard SVM regression is formulated as follows:

$$\min J(w,\xi)=\frac{1}{2}w^T w+c\sum(\xi_i+\xi_i^*) \tag{4}$$

Subject to:

$$\begin{aligned}&y_i-w^T\varphi(x_i)-b\le\varepsilon-\xi_i\\&w^T\varphi(x_i)+b-y_i\le\varepsilon-\xi_i^x\\&\xi_i^x,\xi_i\ge 0,\ i=1,\ldots,l\end{aligned} \tag{5}$$

The saddle point of the Lagrangian gives the solution to this optimization problem:

$$\begin{aligned}&L(w,\xi^*,\xi,a,a^*,c,\beta,\beta^*)=\frac{1}{2}w^T w+c\sum_{i=1}^{l}(\xi_i+\xi_i^*)-\\&-(\sum_{i=1}^{l}a_i((w^T\varphi(x_i))-y_i+b+\varepsilon-\xi_i))-\\&-(\sum_{i=1}^{l}a_i^*(y_i-(w^T\varphi(x_i))-b+\varepsilon+\xi_i)-\sum_{i=1}^{l}(\beta\xi_i-\beta_i^*\xi_i^*)\end{aligned} \tag{6}$$

(Minimum concerning elements w, b, ξ_i^* and ξ_i, and maximum concerning Lagrange multipliers $a_i\ge 0$, $a_i^*\ge 0$, $\beta_i\ge 0$, $i=1,\ldots,l$. From the optimality conditions

$$\frac{\partial L}{\partial w}=0,\ \frac{\partial L}{\partial b}=0,\ \frac{\partial L}{\partial\xi_i^*}=0,\ \frac{\partial L}{\partial\xi_i}=0 \tag{7}$$

we have

$$\begin{aligned}&w^T=\sum_{i=1}^{l}(a_i-a_i^*)\varphi(x_i),\ \sum(a_i-a_i^*)=0,\\&c-a_i-\beta_i=0,\ c-a_i^*-\beta_i^*=0,\ i=1,\ldots,l\end{aligned} \tag{8}$$

Based on Mercer's condition, we define kernels:

$$K(x_i,x_j)=\left\{\varphi(x_i),\varphi(x_j)\right\} \tag{9}$$

By (6), (8), and (9), the optimization problem can be rewritten as:

$$\begin{aligned}&w(a,a_i)=-\frac{1}{2}\sum_{i=1}^{l}(a_i-a_i^*)(a_j-a_j^*)K(x_i,x_j)+\\&+\sum_{i=1}^{l}(a_i-a_i^*)y_i-\sum_{i=1}^{l}(a_i-a_i^*)\varepsilon\end{aligned} \tag{10}$$

Table 1: Input and output parameters used for estimation of rock joint trace length by SVM modeling (Igneous rock)

Type of Data	Parameter	Symbol	Max.	Ave.	Min.	Std. dev.
Input Parameters	Survey Location	SL	3	-	1	-
	Intersection Distance (mm)	ID	153.27	74.31	0	40.26
	Aperture (mm)	A	175	28.92	0.5	41.53
	Dip Direction (Degree)	DD	337	175.57	0	95.5
	Dip Angle (Degree)	D	90	64.74	3	20.94
	Roughness (JRC)	R	20	6.20	1	5.80
	Schmidt Rebound	SR	76	56.13	20	12.63
	Joint Set	JS	5	2.87	1	1.22
Output Parameter	Trace Length (M)	TL	9.67	2.64	0.25	2.19

Table 2: Sample of the dataset used for SVM modeling for estimation of rock joint trace length (Igneous rock)

Survey Location	Intersection Distance (m)	Joint set	Aperture (mm)	Dip Direction (Degree)	Dip angle (Degree)	Roughness (JRC)	Schmidt Rebound	Joint Set Trace Length (m)
1	0.00	4	5	158	64	1	46	0.44
1	3.25	5	1	313	67	1	70	2.17
1	10.26	4	1	115	67	1	44	0.46
1	11.80	4	0.5	173	88	11	74	1.82
1	14.10	2	28	158	30	3	74	2.13
1	17.75	1	52	17	34	1	76	2.98
1	36.40	5	0.5	314	76	1	52	0.75
1	36.45	5	2	314	76	1	52	2.52
1	36.55	5	1	314	76	3	52	0.65
2	6.45	4	4	290	52	1	66	1.68
2	10.90	2	16	180	27	9	76	5.00
2	15.60	1	0.5	15	12	1	68	8.25
2	21.40	1	0.5	8	50	1	60	0.70
2	22.70	2	1	145	38	1	60	0.78
2	23.35	3	7	185	73	3	60	5.70
2	30.92	4	0.5	305	75	1	58	1.74
2	31.25	4	0.5	335	75	1	56	1.08
3	12.50	2	160	108	63	16	60	4.28
3	14.80	2	70	128	80	11	36	1.75
3	15.73	3	25	210	8	3	48	0.53
3	16.05	3	75	210	34	3	50	0.98
3	16.85	2	285	120	77	19	48	4.75
3	21.83	2	42	97	70	9	50	1.20
3	22.18	2	25	98	72	5	58	1.03
3	22.32	2	22	112	72	7	30	0.48

Subject to:

$$\sum (a_i - a_i^*) = 0$$
$$0 \le a_i \le c, i = 1, \ldots, l$$
$$0 \le a_i^* \le c, i = 1, \ldots, l \quad (11)$$

Finally, the nonlinear function is obtained as follows:

$$f(x) = \sum (a_i - a_i^*) K(x_i, x) + b \quad (12)$$

Where:

w – the weighted matrix,
x – the input vector,
b – the biased term,
C – a parameter typically used for creating a trade-off between the generalization and the associated error of the model,
m – the total number of training patterns,
ξ_i^*, ξ_i – slack variables,

ε – the accuracy demanded the approximation,
w^T – the transpose of the vector,
ϕ – the transformation for the independent variable,
$K(x_i, x)$ – the inner product kernel function defined by Mercer's theorem,
b – the bias.

5. Datasets

To achieve the purpose of this paper, three datasets from the sedimentary, igneous and metamorphic rocks were prepared. A database including 1652 joints was collected from the previous joint surveys for all rock types. To estimate rock joint trace length, datasets were randomly divided into training and testing datasets, of which 70% of datasets were considered for training, and 30% were kept for testing the models. In **Table 1,** input and output parameters for the SVM learning model are shown. Also, **Table 2** shows a list of sample data for training the SVM model.

6. Estimation of Rock Joint Trace Length Using SVM

Collected rock joint trace length data affected by the size, censoring, and truncation biases (**Kulatilake et al., 1996; Kulatilake et al., 1993; Cruden, 1977**). By reducing the truncation limit in joint mapping, the effect of the truncation bias can be lessened, thus 0.1m was selected as a truncation limit, and the selected exposure is large relative to the spacing and size of the exposed joints. So, size and truncation biases are not considered. By preparing SVM models to estimate the obscured joint trace length, censoring bias was eliminated. Eventually, the obscured joint trace length was estimated by applying prepared SVM models**. Table 3** shows the summary of collected data to estimate joint trace length.

By digitizing the termination of joints, a better view is obtained from exposure of the joint surveys. Then, R_0, R_1, and R_2 are defined as follows (**Kulatilake, et al., 1996**):

$$R_0 = p/(p+m+n)$$
$$R_1 = m/(p+m+n)$$
$$R_2 = n/(p+m+n) \tag{13}$$

Where:

p, m, and n – the number of joints in which both traces are censored, one end of the trace is censored, and both are observable, respectively.

In **Table 3,** calculated values of R_0, R_1, and R_2 are shown.

The performances of SVM for regression depend on the combination capacity parameter C, ε-insensitive loss function, the kernel type K, and its corresponding parameters. The prediction error is scarcely influenced by C, and to make the learning process stable, a significant value should be set up for C (e.g. C = 100) (**Wang, et al., 2003**). The kernel function includes linear, polynomial, sigmoid, splines, and Gaussian radial basis function (RBF) kernel. For the aim of this research, RBF kernels tend to give good performance under general smoothness assumptions, whose choice of this function is consistent with previous research because it has better efficiency than other kernel functions (**Dibiki, et al., 2001; Han and Cluckie, 2004**) which can be stated as follows:

$$K(x, x_i) = \exp(-((\|x - x_i\|^2)/2\sigma^2)) \tag{14}$$

Where:

σ - the width of the RBF kernel.

A modification process should be used to select the best kernel function until RMSE reaches a minimum threshold. To achieve the paper's purpose, the model with the lowest RMSE and high R^2 is designated as the best model to estimate rock joint trace length. Subsequently, by 0.7949, 0.9414, and 0.8119 values of RMSE and 0.9607, 0.9418, and 0.9577 values of R^2 for igneous, metamorphic, and sedimentary rocks, the best models were prepared. **Figure 4** shows a schematic view of SVM architecture, which is used to estimate rock joint

Table 3: Summary of collected data to estimate joint trace length

Rock Type	Site	Joint Set Number	Number of Joints	Type of Termination			Mean Trace Length (m)
				R_0	R_1	R_2	
Igneous	SI1	5	195	0.12	0.21	0.67	2.59
	SI2	4	201	0.20	0.23	0.57	2.24
	SI3	3	160	0.13	0.18	0.69	5.15
Metamorphic	SM1	3	165	0.40	0.17	0.43	7.59
	SM2	3	210	0.37	0.21	0.42	5.09
	SM3	4	143	0.34	0.10	0.56	2.96
Sedimentary	SS1	4	173	0.27	0.17	0.56	3.37
	SS2	3	224	0.23	0.25	0.52	1.13
	SS3	4	181	0.19	0.19	0.62	2.45

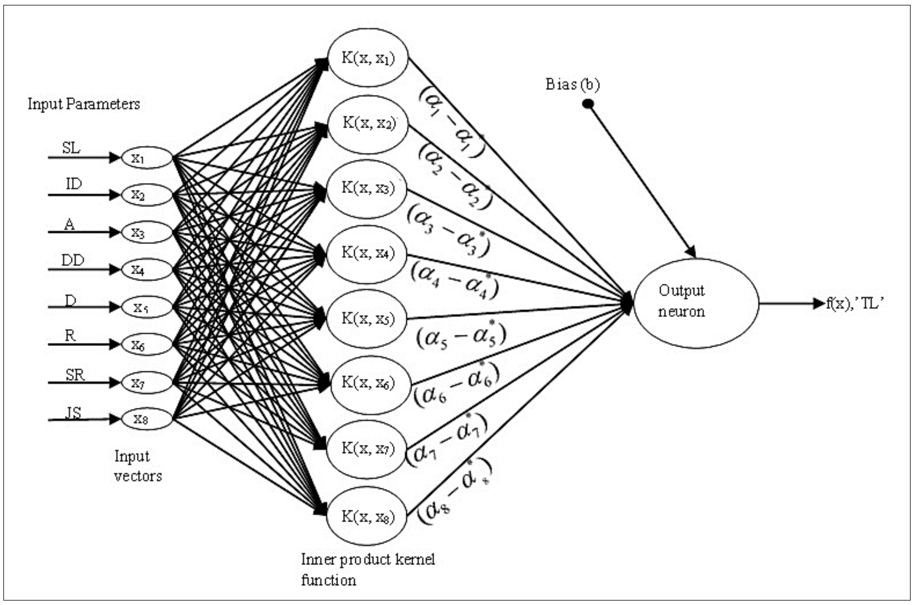

Figure 4: Schematic view of SVM architecture used for estimation of rock joint trace length

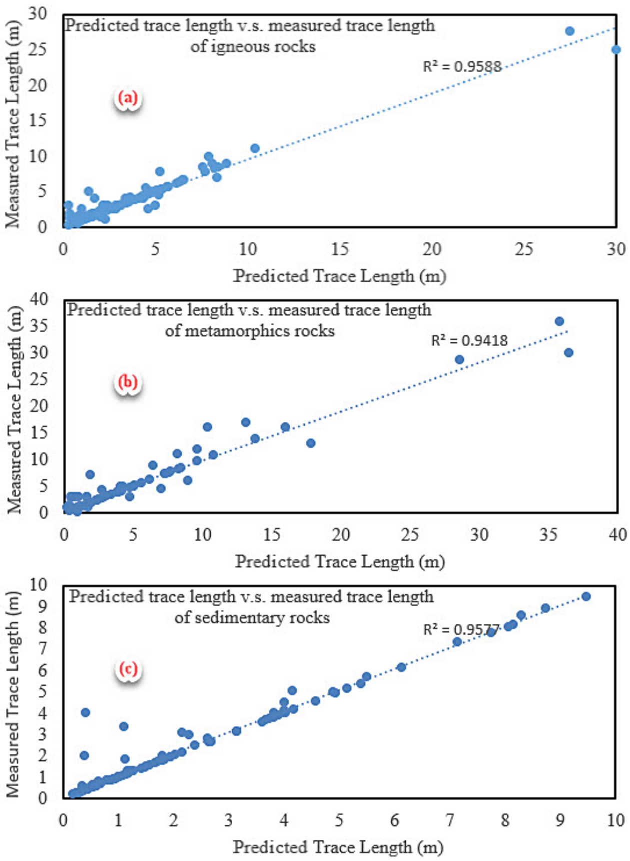

Figure 5: Comparison of estimated and measured data (a) igneous rocks, (b) metamorphic rocks and (c) sedimentary rocks

trace length. A comparison of estimated and measured data is shown in **Figure 5**.

7. Discussions

The material comprising the intact rock is natural and has been subjected in most cases to millions of years of mechanical, thermal, and chemical action. Therefore, throughout the mentioned processes, discontinuities formed inside the intact rocks, and finally, jointed rock masses formed. Discontinuities control the behaviour of structures constructed in and on rock masses. So, all properties of rock joints must be surveyed precisely. The relationship between these properties is highly nonlinear, complex, and difficult to handle with traditional modeling methods. Due to the small size of the exposer, joint trace length cannot be measured accurately because this property has vital importance on the behaviour of rock masses. Therefore, joint trace length must be estimated by prediction methods.

To achieve the paper's goal, by applying SVM learning models, obscured trace length in all surveyed sites was estimated. The mean trace length of each site was calculated again, which, in **Table 4** shows comparisons of measured and estimated mean of rock joint trace length.

Table 4: Measured and estimated mean of rock joint trace length

Rock Type	Site	Mean Trace Length (m)	
		Observed Trace Length	Estimated Trace Length Using SVM Models
Igneous	SI1	2.59	3.82
	SI2	2.24	3.28
	SI3	5.15	5.58
Metamorphic	SM1	7.59	8.02
	SM2	5.09	7.15
	SM3	2.96	3.08
Sedimentary	SS1	3.37	3.63
	SS2	1.13	2.21
	SS3	2.45	3.51

As shown in **Table 4**, the difference between the mean of the measured data and the mean of the estimated data can be seen. Therefore, in the joint survey, if most of the existing joints in the exposure are obscured, the observed mean trace length will not be a good indicator of the mean trace length of the joints. Therefore, estimation methods should be used to predict the actual length of the joint.

The SVM models can generalize a solution from the pattern presented during the training process. Once the network is trained with a sufficient number of sample datasets, predictions can be made based on previous learning. In recent years, an increase in SVMs applications has been observed in rock mechanics, geotechnics, and engineering geology. These applications demonstrate that SVMs are efficient in solving problems in geosciences where many parameters influence the process. Thus, an attempt has been made to develop an SVM model for predicting joint trace length based on the information of joint parameters, which can be measured accurately.

SVM has a theoretical foundation based on the minimization of structural risk. It is better than the routine Neural Network based on the traditional minimization principle of experience risk. SVM arithmetic takes the form of a problem in convex quadratic optimization, ensuring that the solution is optimal. The method resolves practical issues like small samples, nonlinearity, and high-dimensional input spaces. The degree of a problem's complexity does not depend on the dimension of the characteristic equations being optimized. It has an excellent ability to generalize. As a result, using this method can achieve acceptable results with less data.

8. Conclusions

This research estimated obscured rock joint trace length using the support vector machine (SVM) models, a novel machine learning method based on statistical learning theory. To achieve the paper's purpose, the model with the lowest RMSE and high R^2 is designated as the best model to estimate rock joint trace length. In this study, three data sets from the sedimentary, igneous, and metamorphic rocks were organized, with the location of joints on the scanline, aperture, spacing, orientation (D/DD), roughness, Schmidt rebound of the joint's wall, type of termination, trace lengths in both sides of the scanline and joint sets were measured, so by using these rock joint properties, an SVM model was developed. The proposed model predicts the obscured rock joint trace length values simply and cost-effectively by avoiding many destructive, time-consuming and expensive tests, which is very useful during the early stages of engineering design. Subsequently, by 0.7949, 0.9414, and 0.8119 values of RMSE and 0.9607, 0.9418, and 0.9577 values of R^2 for igneous, metamorphic, and sedimentary rocks best models were prepared.

This study demonstrates that the SVM is an excellent method for estimating rock joint trace length using scanline sampling. The SVM transforms the complex and nonlinear rock joint data into a higher dimensional feature space and finds the optimal rock joint trace length estimate. The SVM is potentially an excellent algorithm to improve joint surveys accuracy compared with measured data. Additionally, there will be more profits to obtain accurate data of rock joint properties. Since joint systems in rock masses are geometrically complex, they control the fluid-mechanical behaviours and stability of constructed structures in and on the jointed rock masses. So, obtaining accurate data of joint properties could be very useful in understanding the behaviours of rock masses.

Future investigation will include discovering more applications of SVM-based models in rock mechanics to improve 3D estimation of rock masses.

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SAŽETAK

Procjena duljine traga pukotine razlomljene stijenske mase pomoću algoritma SVM (algoritma stroja potpornih vektora)

Za modeliranje razlomljenih stijenskih masa potrebni su geometrijski parametri pukotina kao što su orijentacija, razmak, duljina pukotine, oblik i lokacija. Duljina pukotine stijene jedan je od najkritičnijih projektnih parametara u inženjerstvu stijena i geotehnici. Ona kontrolira stabilnost nagiba stijene i tunela u razlomljenim stijenskim masama te utjecaj na čvrstoću stijenske mase. Obično se utvrđuje terenskim istraživanjima. Istraživanje duljine pukotine zahtjevno je, jer se cjelovita duljina unutar stijenske mase ne može promatrati izravno. Razvoj modela za predviđanje duljine traga pukotine iznimno je važan u inženjerstvu stijena. U okviru ovoga istraživanja predstavljen je algoritam SVM (engl. *support vector machine*, hrv. stroj potpornih vektora) za procjenu duljine pukotine. Riječ je o naprednoj metodi koja se koristi za rješavanje problema maloga uzorka, nelinearnosti i višestrukih dimenzija, s dobrim svojstvima generalizacije problema. Priređena su tri skupa podataka iz taložnih, magmatskih i metamorfnih stijena, koji uključuju položaj pukotina na liniji uzorkovanja, te njihov otvor, razmak, orijentaciju, hrapavost, Schmidtov odbojni test na stijenke pukotine, tip završetka, duljine traga na obje strane linije uzorkovanja i skupove pukotina. Rezultati predloženoga algoritma pokazuju podudarnost predviđenih i izmjerenih rezultata dobivenih terenskim istraživanjima. Rezultati pokazuju da je predloženi algoritam vrlo učinkovit u predviđanju vrijednosti duljine traga pukotine stijenske mase. Njegovim korištenjem može se dobro procijeniti stvarna duljina traga pukotine te izbjeći skupa, teška, dugotrajna i agresivna istraživanja razlomljenih stijenskih masa.

Ključne riječi:
izloženost stijenske mase, duljina traga pukotine, linija uzorkovanja, SVM algoritam

Author’s contribution

Jamal Zadhesh (Student, Ph.D., Mining Engineering) provided the interpretations and wrote the manuscript. **Abbas Majdi** (Professor, Ph.D., Mining Engineering) provided the interpretations and presentation of the results.