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RESEARCH ARTICLE

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# Establishing the Gap Between Manually Picked and the Predicted Seismic Velocity

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**Abstract:** In exploration seismic, the seismic velocity is the key to delineating many physical properties of the subsurface. There are ways to calculate the velocity and, most popularly, it is picked manually for any seismic project. The velocity picking method has a few limitations when it comes to its quality, time consumption in this process, and the money spent during the whole work. The main objective of this paper is to provide velocity estimation of the respective region (three-dimensional seismic) derived from the velocity field available in the region from a few 2D seismic lines. The purpose is to avoid manual velocity picking errors and make the overall velocity in the region more geologically consistent with the surrounding data. Even more importantly, a seismic velocity volume assessment model created through this technique can also support any future 3D seismic imaging.

**Keywords:** seismic velocity, 2D, 3D, Geoscience Australia, velocity picking, marine

## 1. Introduction

The sole purpose of seismic exploration is to image the earth's interior, where the velocity of seismic waves is the vital element [1]. Starting from 2D seismic data acquisition, the industry has come a long way in the last few decades. The 2D seismic data acquisition and its imaging has always been a challenge. The out of plane energies, diffractions, and multiples have always made it difficult to clean the seismic dataset at pre-processing stages. This also affects the appropriate velocity estimation in the 2D seismic dataset. The inaccuracy in the velocity leads to a geologically incorrect positioning of the geological structures, which causes a discrepancy in the final imaging of the data. It is also not very easy to pick velocities on a 2D seismic data compared to the 3D seismic data. These challenges exist in all 2D seismic datasets be it land, marine, or transition zone data acquisition. Velocity computations are made methods based on analysis of seismic data [2]. A detailed and accurate velocity helps to extract precise subsurface imaging of seismic data. This provides an accurate structural interpretation and then subsequent research or associated study of the area.

The manual velocity estimation with the help of seismic data has been both expensive and time consuming [3]. Velocity picking requires people with extensive experience in seismic data processing and a good understanding of geology as well as the behavior of seismic waves [3].

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To increase efficiency and reliability and save time and keep velocity picking inexpensive, it is important to find an effective and relatively fast method for automatic velocity picking [4].

Ji et al. [5] proposed a method of velocity interpolation with the help of existing structures in the seismic and, to do so, Ji et al. [5] picked sparse velocity in the study and then performed structure-oriented velocity interpolation (SOVI). The method was used to interpolate 3D seismic velocity with sparse 3D seismic velocity as a guide. Based on the method proposed by Ji et al. [5], the authors are proposing the velocity estimation of a 3D seismic volume based on the surrounding 2D lines. The purpose is to avoid picking velocities if we have enough velocity information from nearby lines. A seismic velocity volume created through this technique can also support any future 3D seismic imaging. This method can be extended to more nearby datasets and can be used as a regional velocity for future use.

The proposed method in this work estimates the seismic velocity of the study area and its surroundings, this helps to address if there is a picked 2D seismic velocity anomaly. This also helps to improve the seismic data processing processes directly associated with velocity estimation, like de-multiple, migration, etc [6].

Having a 3D image is always useful for the presentation and interpretation purpose in any seismic study. It brings precision to drilling even in complex geology [7]. The final 2D imaging often get affected by the off-plane 3D effects. The proposed method helps in getting rid of such anomaly as well as it reduces the weeks of hard work of manual velocity picking to a few days of work of either same or better a quality output.

For any geological area, be it new or already explored, if there is an existing 3D imaging or 3D-velocity volume, then it is always useful for further work or reference. A 3D subsurface attribute talks more about the regional geological settings beneath earth [7]. An existing or easily derived robust 3D velocity volume can save thousands of dollars of manual velocity picking for any 3D or 2D seismic of the study area and can save many weeks of time used in manual picking.

## 2. Literature Review

The literature review for this work considers many works done to estimate the seismic velocities. Chen and Sidney [8] mentioned that seismic attributes can be classified as either horizon-based attributes or sample-based attributes. Most of the work is done on only sample-based attributes. Hampson et al. [9] proposed the conventional crossplot method to estimate sample-based seismic attribute. Schmidt and Hadsell [10] as well as Fish and Kusuma [11] developed automatic velocity picking methods that were based on neural network. Later, with the use of the neural network, Calderón-Macas et al. [12] proposed a simulated annealing technique, Smith [13] proposed a clustering algorithm, Ma et al. [14] proposed a convolutional neural network, and Biswas et al. [15] proposed a recurrent neural network. These methods are capable of picking velocity automatically, but the stacking velocity estimation by these works is not very accurate. This is simply because the simple neural network models do not have a very strong learning capacity [16]. Pedersen-Tatalovic et al. [17] presented a work based on horizon-based attribute and modeled seismic attribute porosity for a small 3D area.

All these works were carried out on 3D seismic dataset. Apart from the above-mentioned work, Whiteside et al. [18] worked on creating 3D seismic volume from a set of 2D seismic lines. Duchesne et al. [19] worked on Kriging with an external drift (KED) method to improve seismic velocity for a 2D line.

The work done by Whiteside et al. [18] is creating a 3D imaging volume from several imaged 2D lines. The process was tested on some field examples. Duchesne et al. [19] showed how the KED approach is better than linear interpolation for one line and the work is important for the presented work because it talks about the importance of vintage datasets and its significance for the future work of exploration in new areas. However, Yao et al. [20] showed in their work that the Kriging algorithm struggles without any guidance of structural information. Hale [21] proposed a blended neighbor interpolation that was based on image-guided interpolation for geophysical properties that can be extended to seismic velocity. Zabihi Naeini and Hale [22] advocated for an extension of image-guided interpolation, but they also require interpreted horizons to help stabilize the interpolation for poor seismic.

Ji et al. [5] suggested a combination of several works. In this work, picked velocities were considered as seed points and are then interpolated (and extrapolated). These seed points belonged to a 3D volume, and the output was a fully populated 3D velocity cube with values at each grid point. This approach is fully automatic and completely driven by the structure-oriented smoothing process.

Based on the guidance from above literatures review, the authors used SOVI proposed by Ji et al. [5] and worked on horizon-based attributes (seismic horizons) and sample-based attributes (seismic velocity) for the input 2D dataset to predict the 3D dataset.

### 2.1. Theoretical framework

Interpolation is always required to get the measurement of any attribute in geophysical exploration.

We can assume a set of $K$ known samples as:

$$\mathcal{F} = \{f_1, f_2, \ldots \ldots \ldots \ldots, f_K\} \tag{1}$$

for $f_k \in \mathbb{R}$, that corresponds to a set

$$\mathcal{X} = \{x_1, x_2, \ldots \ldots \ldots \ldots, x_K\} \tag{2}$$

of $K$ known sample points $x_k \in \mathbb{R}^n$.
We can make a set from these two sets as:

$$\mathcal{K} = \{(f_1, x_1), (f_2, x_2), \ldots, (f_K, x_K)\} \tag{3}$$

of $K$ known sample. These $K$ samples are scattered and the scattering in a way that the n-dimensional sample points in the set $\mathcal{X}$ may have no regular geometric structure. The interpolation problem is to use the known samples in $\mathcal{K}$ to construct a function $q(x) : \mathbb{R}^n \to \mathbb{R}$, such that $q(x_k) = f_k$.

There exists an infinite number of functions $q(x)$ that satisfy the conditions of the interpolation $q(x_k) = f_k$. Hence, this problem has no unique solution.

Hale [21] proposed an image-guided interpolation by using blended neighbor interpolation in two steps.

**Step 1:** solving the Eikonal equation:

$$\nabla t(x).\mathrm{D(x)}.\nabla \mathrm{t(x)} = 1, \quad x \notin \mathcal{X};$$
$$= 0, \quad x \in \mathcal{X}; \tag{4}$$

for,
$t(x)$: the minimum travel time from $x$ to the nearest known sample point $x_k$,
and
$p(x)$: the value $f_k$ corresponding to the sample point $x_k$ nearest to the point $x$.

**Step 2:** solving the smoothing equation

$$q(x) - \frac{1}{2}\nabla.\, t^2(x)\mathrm{D(x)}\nabla q(x) = p(x) \tag{5}$$

for $q(x)$

The $D(x)$ is a metric tensor field. It contains spatially varying coefficients.

## 3. Research Methodology

### 3.1. Research design

The data used for the research work are open file data and are freely available for anyone to download from the Geoscience Australia's seismic library (https://nopims.dmp.wa.gov.au/nopims). A total of 73, 2D seismic lines belong to the same geological area were used. These multi-vintage seismic lines belong to 12 different seismic surveys conducted between the year 1973 and 2013. The data acquired over these four decades have impacted a lot on the data quality because of the technological evolution of four decades. But geology, i.e., the subsurface structure and its physical properties, almost remains the same [23].

The data used in this work are 2D seismic; therefore, the authors framed the 2D seismic attributes into 3D seismic attributes. The 3D seismic grid was defined to perform the research work and consequently, the data of the 2D seismic were mapped to the defined 3D seismic grid based on the geospatial positioning (X and Y coordinates) of the seismic, velocity, or structural dataset.

Based on the data under consideration, the authors have extended and "built upon" the approach of Ji et al. [5] to predict the velocity for the best possible imaging of the earth's internal structure. In this research work, the input dataset is 2D and then the 2D dataset was used to populate as a seed point in a defined 3D area covering all the 2D dataset under consideration. A 3D velocity cube with values at each grid point was predicted from the 2D velocity functions.

The SOVI method proposed by Ji et al. [5] can be summarized in the following steps:

1) Computation of structure
2) Initial 3D picked velocity
3) Directional filtering along structural dip.

Reflection and transmission are inherent properties of a seismic wave when it hits an interface. The reflection and transmission process takes place differently for different subsurface geological settings. The seismic acquisition direction affects the reflection and attenuation of seismic waves [24]. Therefore, the different 2D vintages of seismic data will have a combination of seismic data traveled with distinctive reflection and attenuation than any 3D seismic data acquired at once. Also, these velocities are from different vintages that were estimated over relatively different seismic data and therefore may not always be the best estimate.

Note that in the work of Ji et al. [5], they had their data from a single seismic data acquisition, therefore for any existing bias in their dataset can make the whole output affected by the bias [25].

Ji et al. [5] used their study data from 3D land seismic data. The geophysical challenges in land seismic data acquisition are always a great deal compared to the marine seismic data [26]. The imaging of any horizon in marine seismic data is almost always better than land seismic. The reflection is always poor in land seismic when compared to the marine seismic and therefore a velocity estimate in marine seismic will always be a better estimate in marine seismic data when compared to land seismic data [27].

## 3.2. Research procedure

The data under study went through pre-processing and after thorough analysis 73 lines were selected within an area that was considered as the final extent of 3D volume.

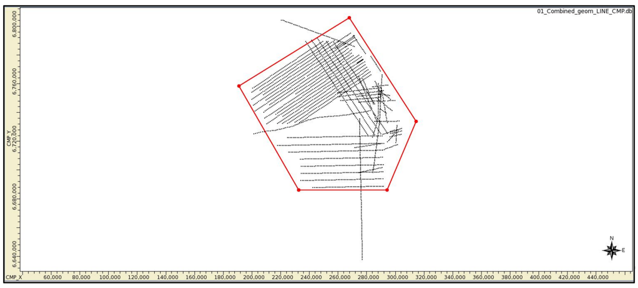
Figure 1 shows an example of a velocity for a 2D line defined by location and the values of velocity at different times at the location 780.

With these velocity profiles for the 72 lines, we mapped them on their geospatial location. On the surface, each velocity location is considered as a point in the dataset and these points are at an interval of 1 km to the nearby velocity location of the same line (Figure 2). A polygon was defined to select the data for conversion from 2D to 3D (Figure 2).

**Figure 1**
**Example of a velocity dataset for a 2D line**

| CMP | TIME | VRMS |
|---|---|---|
| 620.0 | | |
| 780.0 | | |
| | 49.34 | 1502.0 |
| | 141.7 | 1881.0 |
| | 234.3 | 2113.0 |
| | 334.6 | 2301.0 |
| | 427.2 | 2378.0 |
| | 562.2 | 2445.0 |
| | 751.2 | 2589.0 |
| | 948.0 | 2754.0 |
| | 1083.0 | 2909.0 |
| | 1280.0 | 3053.0 |
| | 1469.0 | 3197.0 |
| | 1612.0 | 3374.0 |
| | 1821.0 | 3619.711374457461 |
| | 2404.0 | 4128.0 |
| | 2596.0 | 4269.91659867382 |
| | 3014.0 | 4518.0 |
| | 3950.0 | 4895.0594331091515 |
| | 4586.0 | 5072.289085505959 |
| | 5755.0 | 5330.302397910568 |
| | 6534.0 | 5467.018814317397 |
| | 7605.0 | 5626.262728788946 |
| | 8470.0 | 5738.244298819962 |
| | 9199.0 | 5826.585851701545 |
| 940.0 | | |
| 1100.0 | | |
| 1260.0 | | |
| 1420.0 | | |

**Figure 2**
**2D dataset data under consideration with polygon**

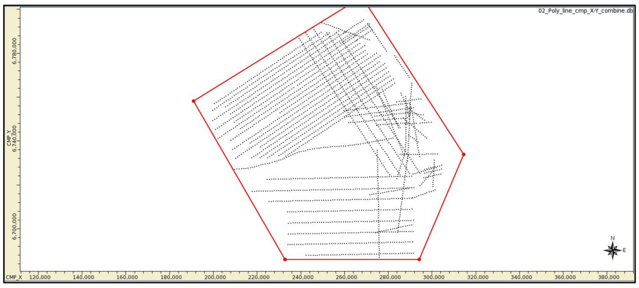


The data beyond the polygon were removed from the study because this extension is a representation of only a 2D dataset in the absence of more seismic lines (Figure 3).

Note that within any 2D seismic line, the velocity locations are 1 km apart, but any two seismic lines are neither of same length nor always parallel and equidistant. There are lines that intersect each other as well.

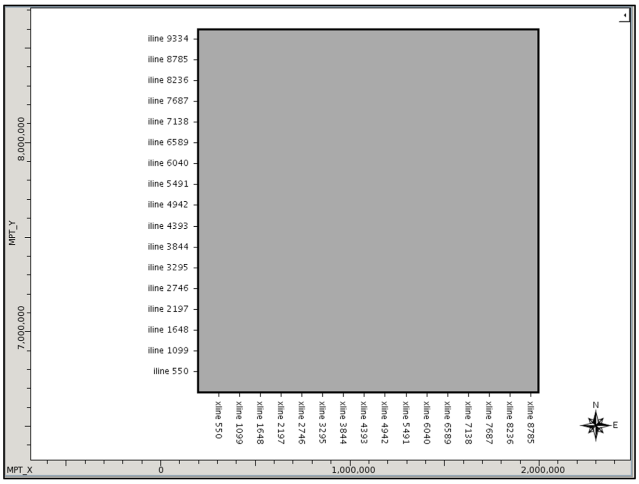
A 3D seismic grid [6] was defined based on the X and Y coordinates of the seed points. The 3D grid was defined as

**Figure 3**
**Defined 3D area from the selected 2D dataset**



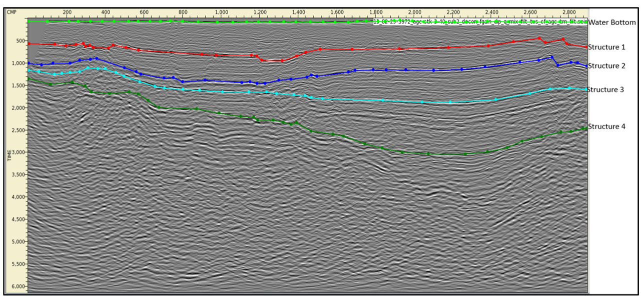
200 m × 200 m cells. This means the final 2D velocity volume will have a velocity location at every 200 m in each direction (North, South, East, and West). The 3D grid definition also converts the X-Y coordinates into an inline-crossline (inline – xline) defined grid. Figure 4 shows an example of a 3D grid of 200 m × 200 m with defined inline-crossline and their X-Y coordinates.

**Figure 4**
**Defined 3D area from the selected 2D dataset**




The next step is to consider the horizon-based attribute. Water bottom is the first and most important structure in marine seismic that separates the earth's crust from ocean water [6]. Figure 5 shows that, along with the water bottom, four more structures were defined to

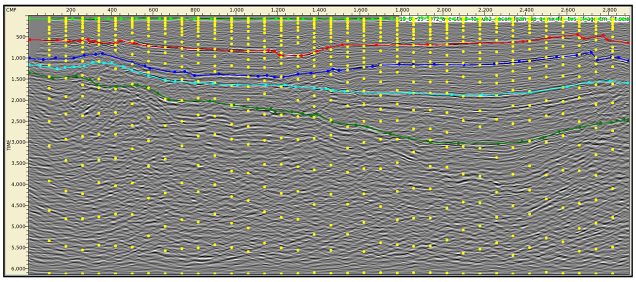
**Figure 5**
**Seismic section with structures**




guide the velocity interpolation within a line. It is important to have important structures defined, this will help even if the seismic data do not have a high resolution, then having these horizons for all the lines would help in stabilizing the velocity prediction across the area.

Figure 6 shows the time-consuming, manually picked 2D seismic velocity at respective locations along with the four horizons. Figure 6 is a display of sample-based and horizon-based attribute on a seismic section.

**Figure 6**
**Velocity and horizon display**



The manually picked velocities and structures of 2D were used as seed points after repositioning them into the defined 3D grid and then into fully populated grid points of 3D volume of velocity and horizons for all the dataset under consideration.

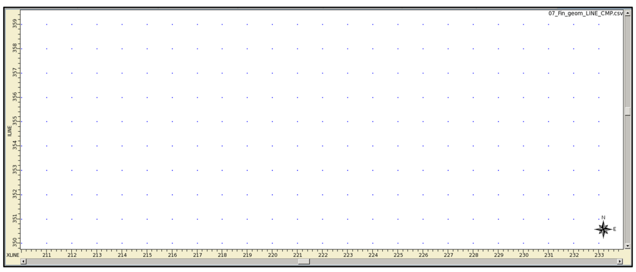
The next step is the structural velocity interpolation of the velocity. The structural velocity interpolation considers the dip of the dipping structures within the data and, the dip is basically the change in the structure over distance [28]. With the data ready to train the regression model with the predefined velocity ranges to be populated over the 3D volume, we have

1) Structural information over the complete available dataset in the 3D volume
2) Velocity seed populated over the 3D grid.

Now we can apply directional filtering on velocities over the structures in the 3D domain and use anti-leakage Fourier transform method [29] for the regression model of velocity prediction across all the 3D bin for one velocity location in each bin along with SOVI to the whole 3D dataset. Figure 7 is a zoomed display of the position of each velocity location at 200 m in each of the four directions (North, South, East and West).

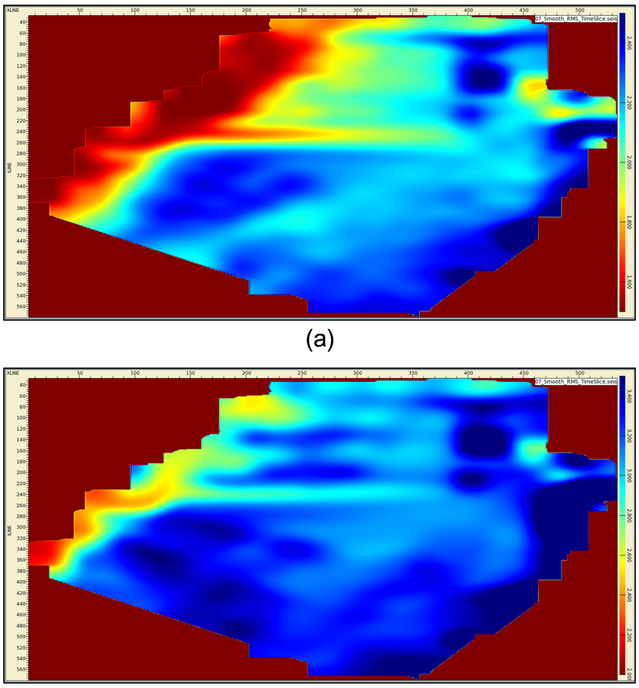
Oppermann et al. [30] proposed a TimeElide, which can be used as an analysis tool for a time-value pair of attributes. This visualization is

**Figure 7**
**Velocity location at 200 m × 200 m 3D grid**



also known as time slice. A time slice visualization of 3D data gives the values of an attribute under consideration at a constant time over the spread of X and Y coordinates [31]. A change in the attribute denotes a change in structural pattern. The change in velocity of the following structures was observed on time slices taken over different times. Figure 8 shows the time slices of predicted velocity values at different times (shallow to deep).

**Figure 8**
**(a) Predicted 3D velocity volume at time 500 ms and (b) predicted 3D velocity volume at time 2000 ms**



(a)

(b)

The color bar is shown for the velocity value range, and we cannot use a constant velocity colormap because the velocity values are continuously increasing because the seismic wave velocity continuously increases with depth [32].

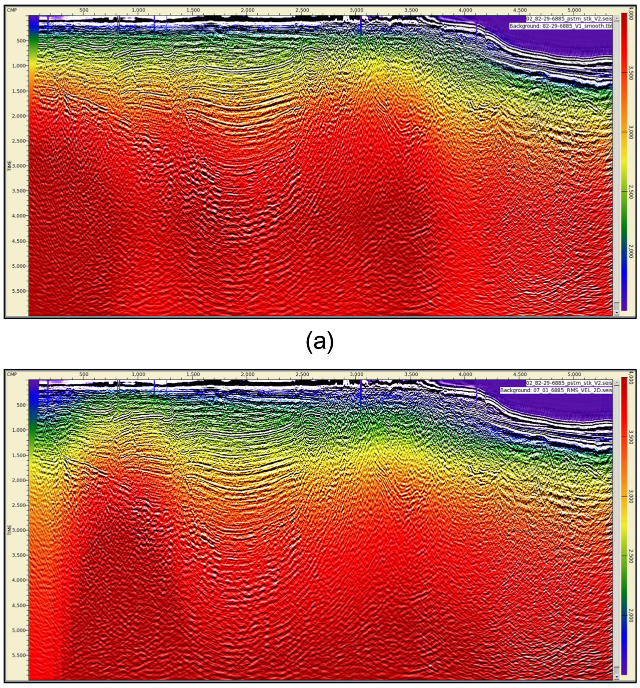
## 3.3. Ethics statement

The data under consideration come from the analysis of the open file dataset from the data repository of Geoscience Australia. If data are categorized as an "open" dataset, it means that the data are available for everyone for use or access and the data are also available to share. The Australian government encourages all its agencies to make their data available publicly [33]. Therefore, the data used in this research work are freely available to download. We do not need any permission to work on this data. Also, the research work was done in the absence of any kind of commercial or financial relationship with any party. This keeps us safe from any potential conflict of interest.

## 4. Results

Figure 9 shows the original and predicted velocity values over a randomly selected 2D seismic line. The test results from Figure 9

**Figure 9**
**(a) Original picked 2D velocity overlayed on seismic and (b) predicted velocity overlayed on seismic**



(a)

(b)

show that the defined SOVI model can accurately pick the time-velocity function that follows the geology of the data. The intelligent prediction results are not very different from that of manual picking. These seismic images have consistent structural information.

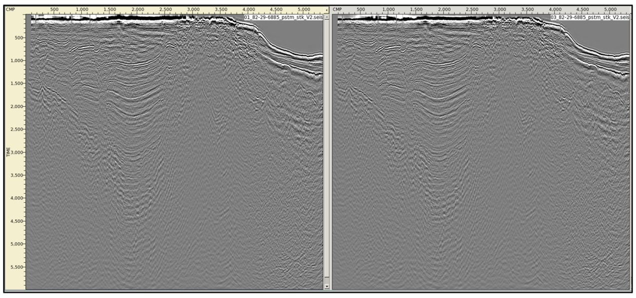
Also, at the start of the line (left side of the image), the overlaid velocity does not look as good as it is for the rest of the line. This is caused by the edge effects, where not enough seeds are available to train the program for a structurally consistent velocity prediction [34].

Except for the edge effect, the predicted velocity function over the complete line looks more structurally consistent with that of manual picking shown in Figure 9(a).

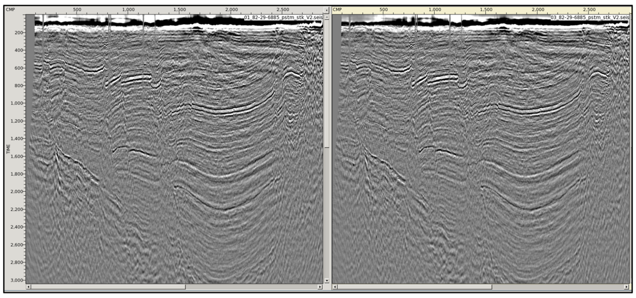
To verify the quality of the interpolated velocity, we will do the final imaging of the 2D seismic for both velocities. The final imaging is basically a process to replace the reflection events with their true subsurface locations on the seismic section, this process is called migration [35]. Figure 10 shows the imaging result from the two velocities. The image at the left is from the original picked 2D velocity, and the image at the right is from the predicted velocities.

The detailed and local structures, like the deep high-velocity structure (Figure 10(a)), the shallow weak reflection (Figure 10(b)), and the mid-detailed high amplitude structure (Figure 10(c)), are also well-imaged by using our prediction method. The imaging with the predicted velocity confirms that the imaged seismic structure is similar and can be used for further exploration work.

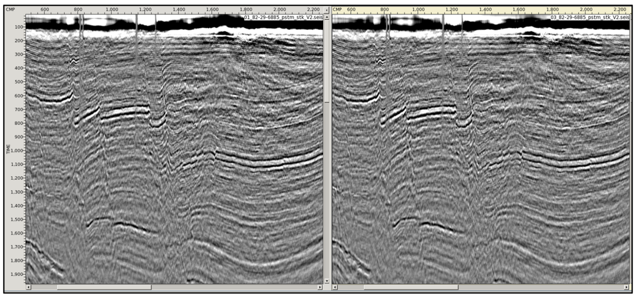
**Figure 10**
**(a) Both imaging output look almost similar, (b) the edge effect on velocity translated on imaging, and (c) almost similar imaging of fine geological details**



(a)



(b)



(c)

## 5. Discussion

The quality of the seismic image can be limited by the edge effect, and therefore, a real 3D input will always be relatively better imaged than a 2D. When it comes to imaging seismic data, 2D imaging always struggles to position the seismic reflection at its place; therefore, seeds from 2D velocity may not always be the best starting point. But the SOVI method considers the structural dipping in all the directions (depending upon the initially available data) and therefore helps to obtain a reliable prediction of the velocity function.

Usually, when velocities are manually picked, the picking process requires extensive human intervention [36]. Hence, it is a labor-intensive, time-consuming, repetitive, and prone to human errors process, and it needs enough time for a large 3D volume or big 2D seismic. The velocity picking is done a minimum of three times in any seismic data processing project. A geophysicist with extensive experience is ideally expected to pick 150–200 velocity locations in a day, depending upon the complexity of the seismic in the study area. Although it is expected to manually pick seismic velocity for almost 150 to 200 velocity locations per day, but it is not achievable if someone is going assiduously through the details of seismic velocity.

**Table 1**
**Estimation of days for manual picking of seismic velocity**

| Seismic | Days for 1 km velocity location | Days for three passes of picking | Total weeks |
|---|---|---|---|
| 1500 | 10 | 30 | 6 |
| 3000 | 20 | 60 | 12 |
| 4500 | 30 | 90 | 18 |

Table 1 presents an estimate of the number of days for velocity picking, where the first column seismic represents the number of locations needed to be picked at an interval of 1 km. Please note that in current times a survey with up to 3000 picks at an interval of 1 km is considered a small survey.

The number of weeks represents how time-consuming is the process of velocity picking. This clearly shows that a 2-km velocity picking will half the time and 3 km will make it one-third. But if we are using 2-km manual picking and then using the SOVI method, then we can make the velocity picking estimate almost five to six times faster.

The velocity prediction with SOVI method after all the necessary input and pre-processing does not take more than a few hours. The pre-processing is dependent on the desired grid of velocity prediction.

The input in the study was spatially irregular because of being 2D. The proposed method can be easily extended to any 3D seismic dataset velocity estimation without going into the hassle of 2D to 3D data conversion. The 3D data input will not create any edge effect because of the regularity in sample point.

## 6. Conclusion

The input data being irregularly sampled did not deteriorate the final prediction of velocities, because of careful pre-processing and data analysis. This shows the preparation of data for initial seed to train the model has played an important role. All in all, the method explained in this work can replace the manual picking of velocity after the sparse initial analysis. This process improves the efficiency of the seismic data processing project, frees up manpower, and significantly enhances the accuracy of predicted seismic velocities. This proposed method has the advantages of automation and efficiency and is extremely easy to implement in any seismic data processing project.

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## Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

## Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

## Data Availability Statement

The data that support the findings of this study are openly available in Australian Government at https://www.finance.gov.au/government/public-data/public-data-policy-initiatives.

## Author Contribution Statement

**Vikash Tripathi:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization. **Michael Baron:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – review & editing, Supervision, Project administration.

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