Machine learning assisted velocity auto-picking

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Summary

Velocity auto-picking can reduce time spent on processing large volumes of seismic data and increase the number of CMP gathers that are picked in a project.

Many velocity auto-pickers have been developed but few, if any, have utilized the power of unsupervised machine learning. Machine learning is an emerging technology for the solution of difficult problems.

A new technique using seismic attributes in conjunction with an unsupervised machine learning clustering algorithm has been developed. The results on both marine and land datasets has shown that this method could potentially reduce the time spent on manual-picking, thus driving down the cost of processing a dataset.

Introduction

Many authors have developed methods in the realm of velocity auto-picking. Semblance-based approaches have been developed (Toldi, 1989) as well as an AVO-based approach (Swan, 2001; Ratcliffe & Roberts, 2003), however each of these approaches has its issues. Semblance-based approaches are very vulnerable to noise in the CMP gathers, whereas testing has shown that the AVO-based approach requires an initial velocity estimate within 5% of the correct velocity.

In Toldi's paper (Toldi, 1989), a semblance-based auto-picker was formed using both semblance and what is referred to as stack power. Stack power is used as an objective function and is maximized with respect to velocity, creating an auto-picked velocity for the entire survey. Differently from the method proposed in this paper, Toldi's method assumes linearization of the model and requires constraints.

In the last several years, machine learning techniques have been employed to address some of the most intractable multidimensional decision problems. This new class of methods has shown promise in areas as diverse as hearing-aid signal improvement, particle physics, and more recently, geophysics (Hijazi et al., 2016; Abazov et. al., 2011; Araya-Polo, et al., 2017).

In this paper, a new semblance-based auto-picking method is described. The method first makes use of many attributes to lessen the noise that a semblance-only auto-picker would struggle with. Next, the best pick locations are determined using a machine learning clustering algorithm. The full methodology and results are described below.

Method

It is well known that semblance-only auto-pickers are too vulnerable to noise and will not give desired results (Toldi, 1989). To develop a semblance-based auto-picker, one must include other attributes that mitigate the impact that noisy CMP gathers have on semblance.

More than 10 attributes were tested in developing the proposed method, but many were found to virtually replicate semblance in performance. Six attributes were eventually settled upon to create a system where noise can be better separated from signal. Once this 6-dimensional space is occupied, the events falling into a select region of the space are projected into the velocity-time plane. The velocity-time distribution is represented by equation 1:

$$P_{ij} = L_{ij} \prod_{k=1}^{k=N} F_k \qquad (1)$$

where F_k represents the filtering coefficient for that attribute, L_{ij} is the location in velocity-time space of that point, and P_{ij} is the projected value of the element in velocity-time space. P is binary and has a value of either zero or one, where points with a value of zero are dropped. Neighboring CMP gathers are used to help reduce the impact from anomalously noisy gathers.

After occupying the velocity-time space with these points, a machine learning clustering algorithm is deployed. The derived cluster centers are then used to map the velocity guide onto a new set of velocity picks.

Attributes

Three categories of attributes are used in this method. First is semblance, which is essentially a measure of coherence across offsets. The more coherent a CMP gather is after NMO, the higher it will be in Semblance.

Another attribute that is considered is the AVO auto-picking method. This method is based on Swan's method for residual velocity analysis using the AVO intercept and gradient traces (Swan, 2001). The intercept and gradient traces are used to compute a "residual velocity indicator" (RVI) trace, which is then used to compute a new velocity table. Due to the requirement that the initial velocity guess be within 5% of the correct velocity, this attribute is optional.

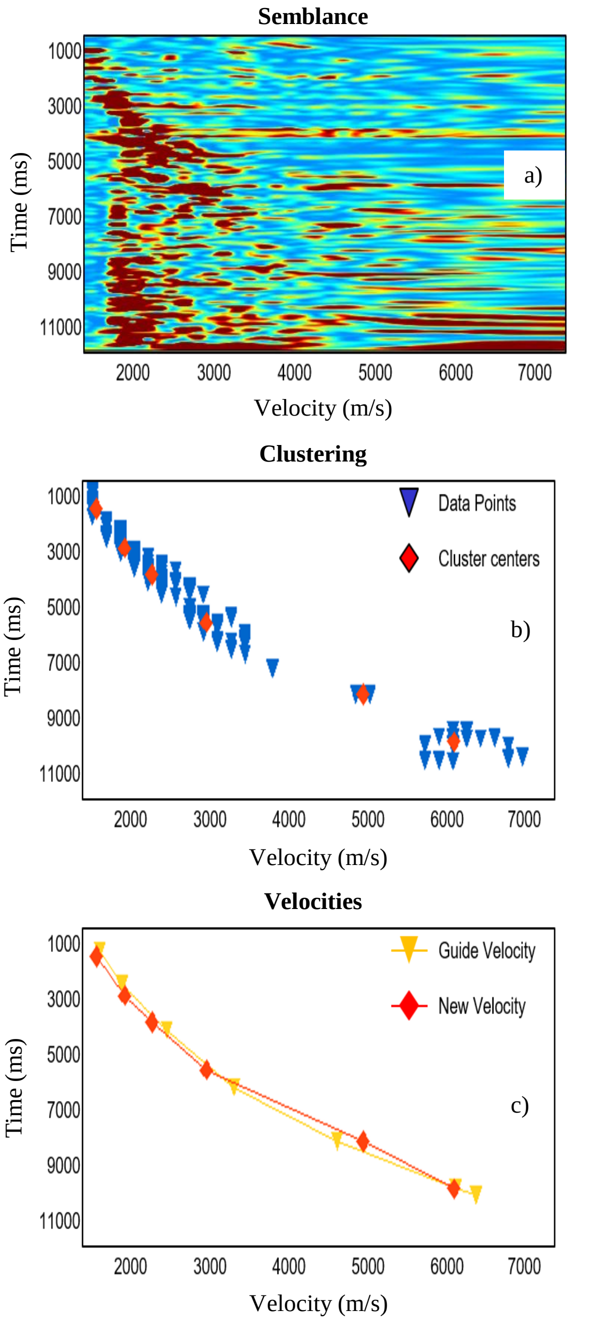

Figure 1: a) semblance of CMP gather, b) clustering of attributes with cluster centers and c) guide velocity with machine learning picked velocity

Finally, two attributes that measure the continuity of a gather across offset are used. These have some similarities to semblance, but are not completely correlated. In the marine dataset shown in the next section, a filter on all attributes contains on average 60% of the number of events that would result from filtering the semblance alone. For the land dataset, as few as 30% of the events that pass through a semblance-only filter pass through a filter of all attributes.

Clustering

Figure 1 shows a graphical representation of the method. For each sample in the typical marine semblance plot of figure 1a, equation 1 is applied, and each attribute is then filtered. Each filter is set using an input parameter and determines if that point lies within the region of interest for that attribute. In this example, a user could set the parameters such that all red points in figure 1a were given a filter value of 1 and all non-red points were given a filter value of 0, thus eliminating them from the machine learning clustering point set. Figure 1b shows the point set that is used by the machine learning clustering algorithm. The blue points represent the points that passed all the attribute filters and the red points are the cluster centers found by the machine learning clustering algorithm. After the cluster centers have been determined, the final step is to map the velocity guide onto the cluster centers. Figure 1c shows the velocity guide in yellow along with the resulting velocity mapping onto the cluster centers in red. NMO was applied to this CMP gather with both velocities and the results are shown in the next section (Figure 2).

Real data examples

Two examples are shown below for the velocity auto-picker. One example is a CMP shot gather from a marine survey, and the other is a stack of the Teapot Dome 3D land survey (a publicly available survey, see acknowledgements for more information).

For the marine dataset case, Figure 2 shows a CMP gather with NMO applied from a) a velocity function hand-picked at the CMP location, b) a single velocity function picked from the center of the survey, and c) a velocity function from the new velocity auto-picking method using the single-picked function as a guide. The gather from the machine-picked velocity is virtually indistinguishable from the gather with the hand-picked velocity. The CMP gather is 10 km away from the single pick, suggesting that picking can be reduced by up to 90% in marine surveys of similar character, while still maintaining a quality velocity model. The difference between the machine learning auto picker velocity and the guide velocity is slightly more than 5% for this gather, making it a good candidate to display the separation power of the new method in an area where the AVO picker is expected to break down.

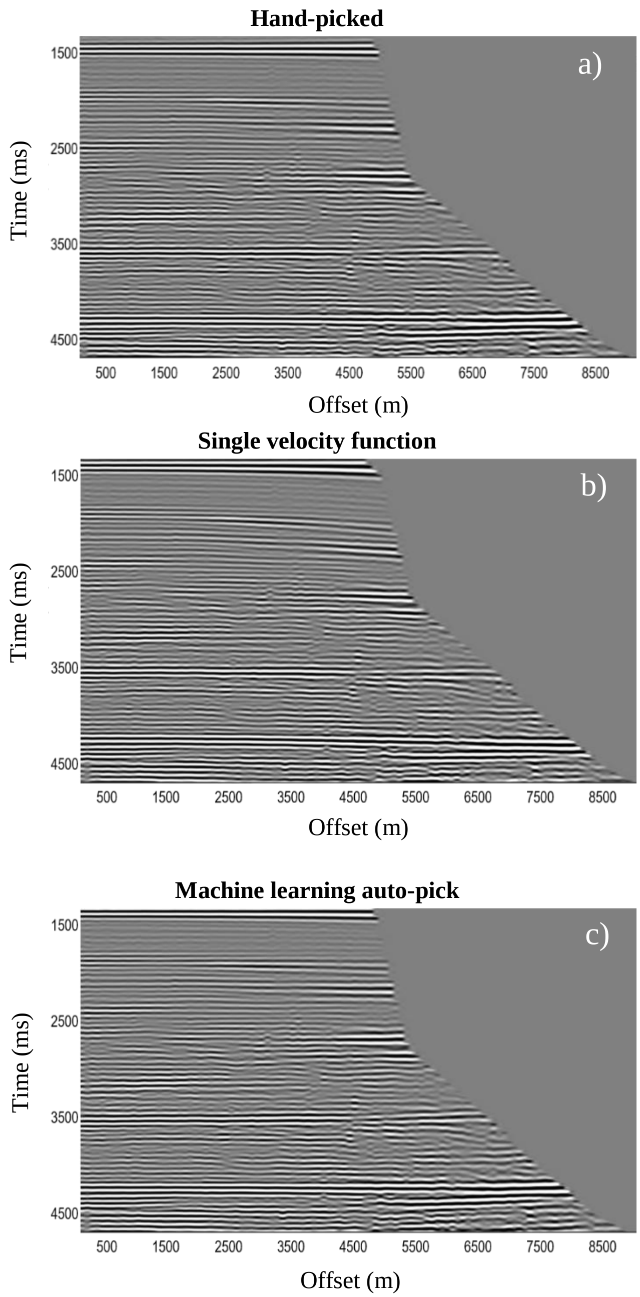

Figure 2: NMO applied to CMP gather with a) hand-picked velocities, b) single velocity picked in center of survey and c) machine learning auto-picker

For the Teapot example, a stack is shown in Figure 3 and stacking velocities are shown in Figure 4 from four different velocities: a) a sparsely-picked brute velocity, b) a semblance auto-picker, c) an AVO auto-picker, and d) the machine learning auto-picker. These velocities were picked prior to any noise attenuation in an attempt to display the power of the machine learning auto-picker. Prior to noise attenuation, semblance-based auto-pickers suffer greatly, as displayed by Figures 3b and 4b. The AVO auto-picker updates the brute velocity (Figure 4c); however, the update is small due to the brute velocities being relatively far from the correct velocity, leading to a marginal change in the stack (Figure 3c). Only the machine learning auto-picker shows a considerable update to the velocity (Figure 4d). These updates lead to a substantially improved stack over the brute stack (Figure 3d). Red arrows are added to the stacks to accentuate the areas where the stack has improved.

Conclusion

Velocity auto-picking is a notoriously difficult problem to solve. Some authors developed modified semblance methods that use attributes in conjunction with semblance to mitigate the issues with semblance-only auto-pickers (Toldi, 1989), while others attempted other methods such as measuring amplitude variations across a CMP gather (Swan, 2001; Ratcliffe & Roberts, 2003).

This new method utilizes both semblance-based auto-picking and AVO auto-picking along with two other attributes to create a modified semblance auto-picker. This unique combination of attributes creates a cleaner point set that has more separation power than semblance alone. Using this point set, an unsupervised machine learning algorithm optimizes new velocity picks.

This method has been shown to be effective in two very different data sets. One dataset is marine, while the other is a land dataset prior to any noise attenuation. These two examples display the potential that this method has in reducing velocity picking time, and in turn, processing cost for a seismic project.

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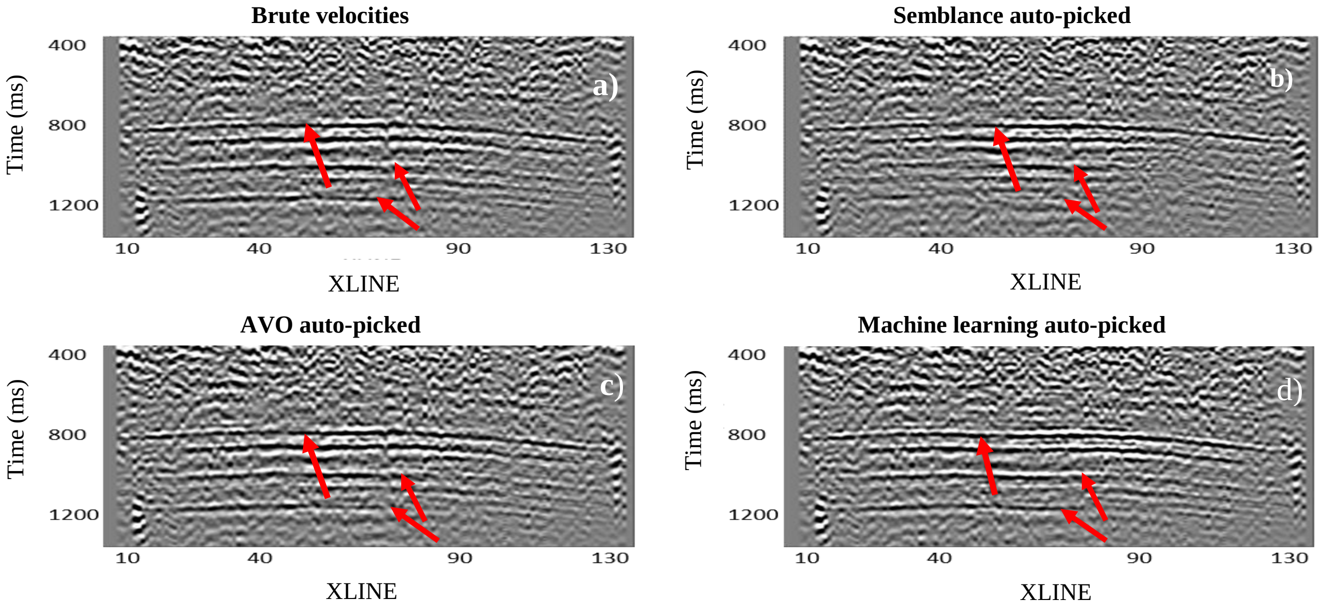

Figure 3: Teapot Dome stack with a) brute velocities, b) semblance auto-picked velocities, c) AVO auto-picked velocities, and d) machine learning auto-picked velocities. XLINE spacing is 110 feet. Red arrows accentuate areas of improvement.

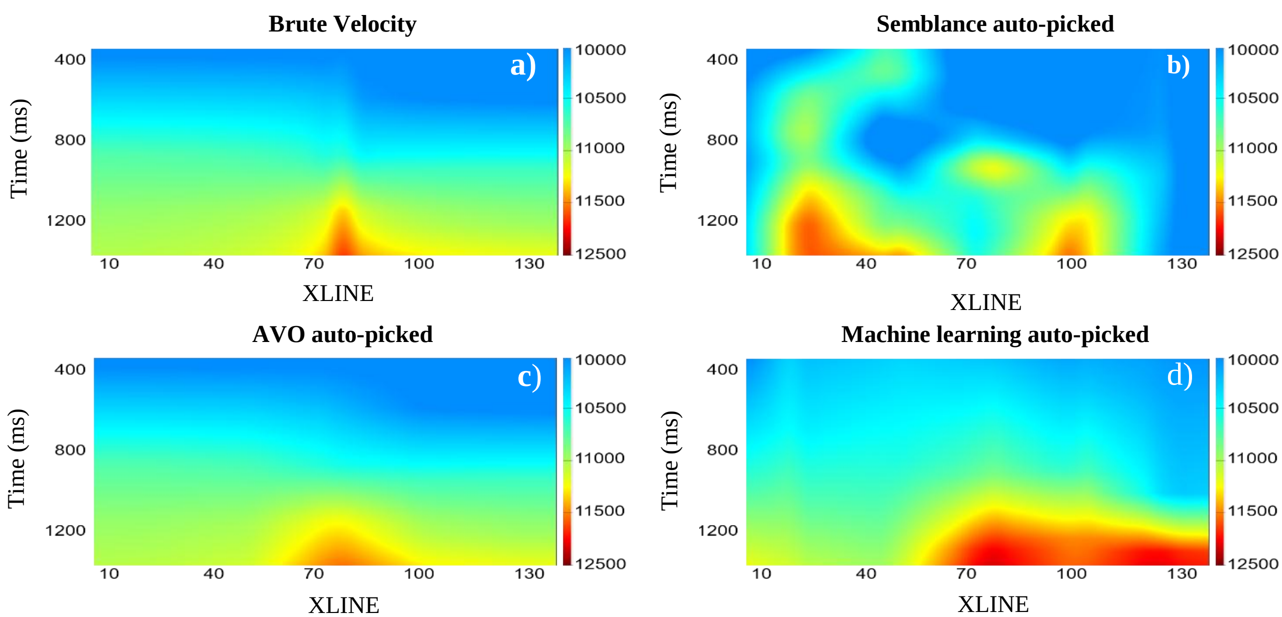

Figure 4: Stacking velocities for a) brute, b) semblance auto-picker, c) AVO auto-picker and d) machine learning auto-picker

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