Automated event picking in prestack hyperspace

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SUMMARY

Seismic data mining is part of an interactive processing and interpretation workflow. The extraction of information will often have the prerequisite of picking reflection events. Methods that aid in automatically extracting information are required when handling large volumes of data. Migrated 3-D seismic data in prestack form (which includes the offset dimension) creates a 4-D hyperspace. An algorithm for tracking prestack reflection events in that hyperspace will be presented. The algorithm combines a range of techniques including supervised learning.

Results of automated picking will be presented for migrated, prestack, field 3-D data. The algorithm was able to track a nominated reflection event in prestack hyperspace from a single seed pick. The results are superior to those produced using a 2-D gather-based approach and a correlation autopicker.

A small number of manual picks are used to train a probabilistic neural network, which assigns each sample an event probability. These probabilities are updated using a set of flow features that propagate seed picks through the hyperspace. Flow features constrain possible picking locations based on inter-relationships with nearby picks and event probabilities in 4-D. The combination of the global 4-D event probability distribution and localised 4-D flow feature updates, creates a highly constrained algorithm. Evolution of a picked event is controlled by quantitative assessment of previously made picks. The algorithm provides a quantitative measure of the reliability of each pick.

Key words: Automatic, picking, prestack, hyperspace.

INTRODUCTION

Interpretation involves integrated induction, reasoning, judgement of contrary evidence and decision-making. Attempts to automate these attributes have been applied in many areas of the seismic workflow. Automation attempts to mimic the logic of human interpreters using numerical processing algorithms. As sophisticated techniques (including pattern recognition, expert systems, artificial intelligence and multidimensional image analysis) continue to develop, so to does the success of automation. However, for most applications completely unsupervised processing is not yet possible, as it is difficult for automatic methods, that are not subjective, to cope with all the complexities of nature. The compromise is interactivity. Automation can be considered as minimisation of this human interaction.

Following the advent of 3-D seismic surveying the geophysicist is routinely faced with processing and interpreting large volumes of data (Herron, 2001). The quantity of data precludes this from being a manual process. As a result, manual interpretations become time consuming, tedious and less constrained, and may be limited by the dimensionality and dynamic range of data displays.

Interactive processing requires the extraction of relevant information from the seismic recordings (such as timing of events or trace attributes). Velocity analysis and tomography, for example, require the picking of prestack reflection events.

The automatic picking method presented here is applied to migrated, prestack data for tomographic velocity model updating. The migrated, prestack data forms a four-dimensional (4-D) hypervolume or hyperspace. A sample in this space is termed a *hyxel* (Lutolf et al., 2002), analogous to the voxel in 3-D and is indexed by three spatial coordinates (being x, y, z of, the common image point (CIP) location) and an offset coordinate (angle of incidence at the CIP in this case).

Glinsky et al. (2001) proposed an algorithm for automatic prestack event picking using a probabilistic neural network (PNN). The applied research discussed here is an extension to this algorithm. Focus will be given to the tracking of events in prestack hyperspace using flow features, which act to constrain the trend of a surface as it is picked. A small subset of manual picks is used to train a PNN, which assigns each hyxel with an event probability. This serves as a prior probability that the hyxel should be picked as a reflection. From nominated seed picks a series of flow features are used to update these priors and predict the location of the next pick in 4-D. These predictions are combined stochastically to make the final pick. A region growing method (that quantifies pick reliability) controlled by the PNN event probabilities of previously made picks is employed. This ensures that, whenever possible, picks with greater certainty are made prior to picks with less certainty.

Autopicking in the prestack domain is complicated by a low S/N ratio (compared to stacked data). The combination of acquisition geometry and subsurface structure can produce moveouts that do not follow hyperbolic curves. Also interference from coherent and incoherent noise can lead to loop skipping which must be corrected manually.

This applied research has novelty over past work (Le and Nyland, 1990; Tinivella, 1998; Di Nicola-Carena, 1999; Zamorouev, 1999). This includes considering migrated prestack data as a hyperspace, the stochastic use of flow features to propagate picks in this hyperspace and the quantification of pick reliability using a PNN.

METHOD AND RESULTS

We apply the method to a prestack, depth-migrated 3-D data set comprising 2891 common image gathers with 15 offsets from 4° to 32° incrementing by 2°. The migration algorithm outputs a sub-hyperspace of prestack data around the horizon under analysis. The sub-hyperspace comprised of 300 depth samples, which equates to 13,000,500 hyxels. This depth window was centred on a post stack pick of the horizon, incorporating 3-D geological structure into the algorithm. Autopicking a nominated horizon was initialised with a single seed pick.

Hyxel Classification

A training set of 395 manual picks was created. This equates to less than one pick per seven gathers. After training the PNN produced a 98% correct classification result with respect to the training picks. For details on the implementation of the training and classification phase the reader is referred to Glinsky et al. (2001).

Flow Features and Propagation Mechanism

The extents of a local event probability region (or *cloud*) are tracked in 4-D from a seed pick based on a user defined event probability threshold. Only hyxels with probabilities greater than the threshold are kept in the cloud. The range of possible picks for an event is the 1-D extent of this cloud on the trace. The probability of each sample in this range is updated by a set of flow features, which independently assign an event probability to each sample in the 1-D cloud. The flow features are presented below.

1) The *PNN event probabilities* derived from training and classification.
2) The *wavelet position* flow feature assigns probabilities based on the difference between the position of a nearby pick on the seismic wavelet as calculated using a combination of the first and second derivatives of amplitude with respect to depth. A sample with a difference of zero would be assigned a probability of 1.0. This feature assumes that as an event is tracked from trace-to-trace, nearby picks will have a similar position on the seismic wavelet.
3) The *pick flow* feature predicts the location of a pick based on the trend of nearby picks. The further away from this predicted location the lower the assigned probability.
4) The *cloud flow* feature predicts the location of a pick based on the trend of the event probability cloud. The further away from this predicted location the lower the assigned probability.
5) The *correlation* flow feature uses conventional cross correlation to assign probabilities.

These features attempt to replicate the thought processes of an interpreter using numerically justifiable procedures. When making a pick an interpreter will consider,

1) the phase he/she is picking (e.g. a trough),
2) the trend of nearby picks,
3) the trend of the wavelet package around the picks,
4) the waveform similarity between traces.

The use of flow features combines all of this information into a single best estimate that is constrained in 4-D.

Flow features are calculated in each direction (defined by a change of one coordinate only) around a trace to be picked. In prestack hyperspace this equates to six possible directions ($\pm x$, $\pm y$, $\pm offset$). All available predictions are combined to produce a final set of updated probabilities for the 1-D cloud on the trace to be picked. The maximum value, selected using cubic spline interpolation, is the next pick. Flow features were given equal weightings in this case.

All adjacent traces around a seed are picked in order of decreasing pick reliability. Each time a new pick is made relevant flow feature predictions are recalculated to take advantage of this new information. When all adjacent traces around a seed have been picked a new seed is selected based on its reliability rank. As soon as a seed with a higher ranking becomes available it will be used to generate new picks. In this way the propagator will preferentially pick areas where confidence is high. This increases the chance of convergence in areas where confidence is low; as they can be constrained using previously made picks.

Picking Results

The evolution of the picked prestack reflection surface is shown in Figure 1. Picks are shown at five stages during the propagation for three different offsets over the entire survey area. The picked surface was generated from one seed pick. The corresponding pick reliabilities are shown in Figure 2. Figure 3 depicts selected gathers highlighting the range of moveouts present in the data. No model assumption is made with respect to moveout during the picking procedure. Figure 4 compares picks made with this algorithm to picks made using conventional correlation. Figure 5 compares the algorithm with a 2-D gather-based version of a similar algorithm. By constraining picks in 4-D loop skipping is avoided and smooth, horizon-consistent picks are produced.

CONCLUSIONS

Migrated prestack seismic data forms a 4-D hyperspace. The stochastic combination of a set of flow features provides a balanced pick-predicting algorithm, which is globally constrained by the extent of event probability clouds, generated by a PNN. The PNN event probability is a useful measure of pick reliability and can be used to quantitatively drive the evolution of the picked reflection surface in prestack hyperspace. A prestack reflection event was accurately picked in 4-D starting from a single seed pick. The algorithm managed a varying S/N ratio and non-hyperbolic moveout to produce a smooth, horizon-consistent surface with no loop skipping.

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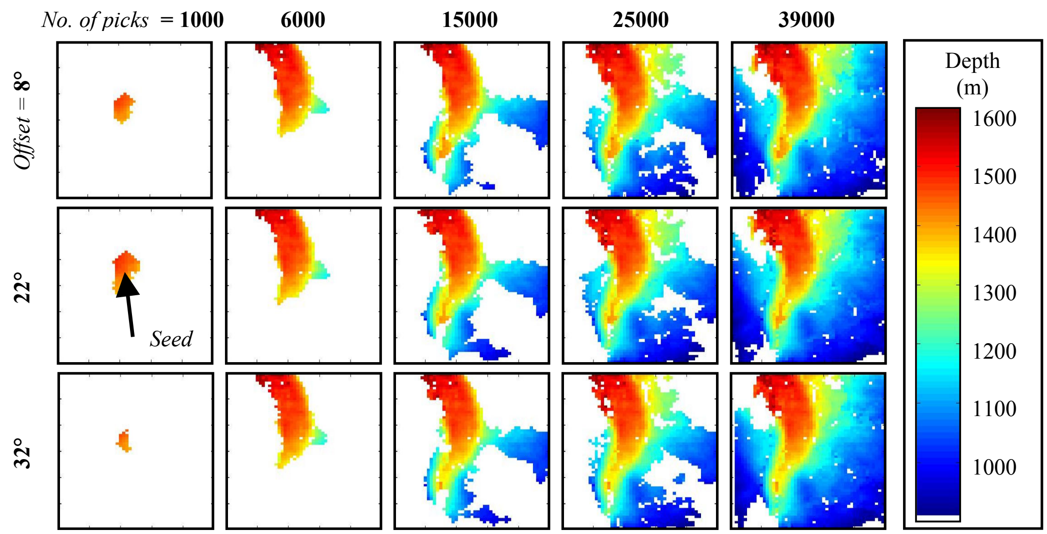

Figure 1. Evolution of the picked reflection event in prestack hyperspace. Areas that have not been picked are shown in white. The picked surface grows in 4-D based on a quantitative assessment of previously made picks.

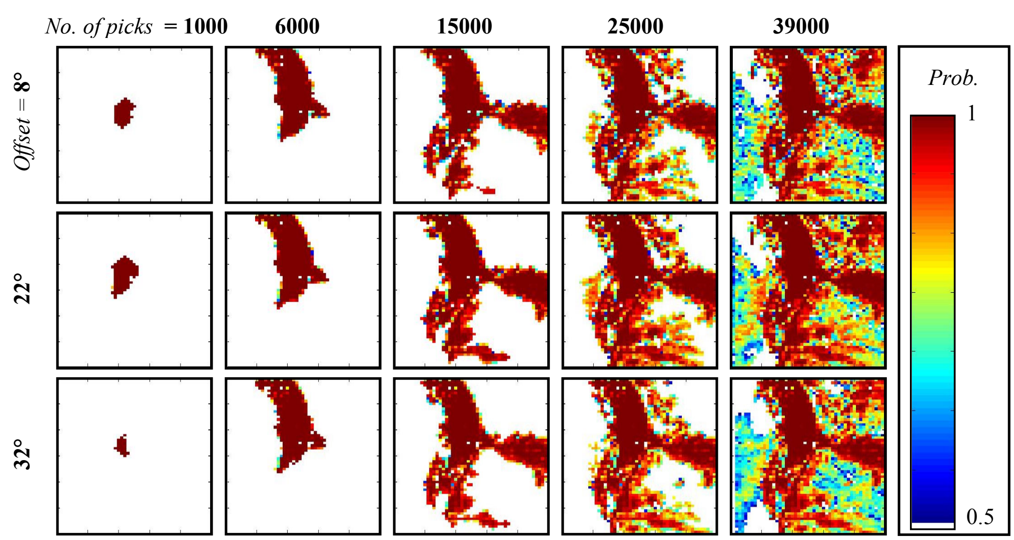

Figure 2. Quantitative assessment of picking results. Picks with the highest quality ratings (red) are picked preferentially. Unpicked locations are shown in white. A threshold of 0.5 has been used. Note the conformance of the probabilities to the stratigraphy in this case.

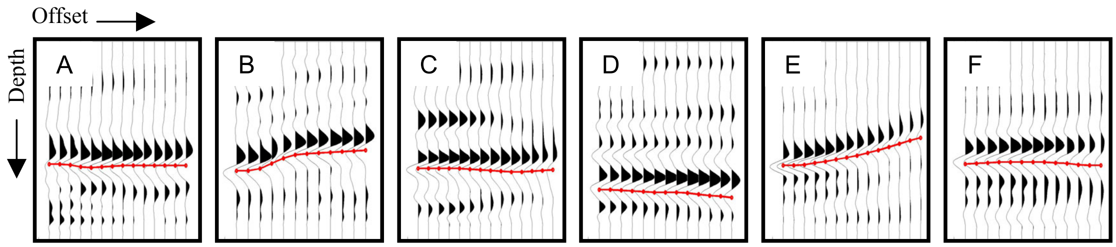

Figure 3. A range of residual moveout trends have been accurately picked. This includes non-hyperbolic trends (B). Autopicked events are shown in red.

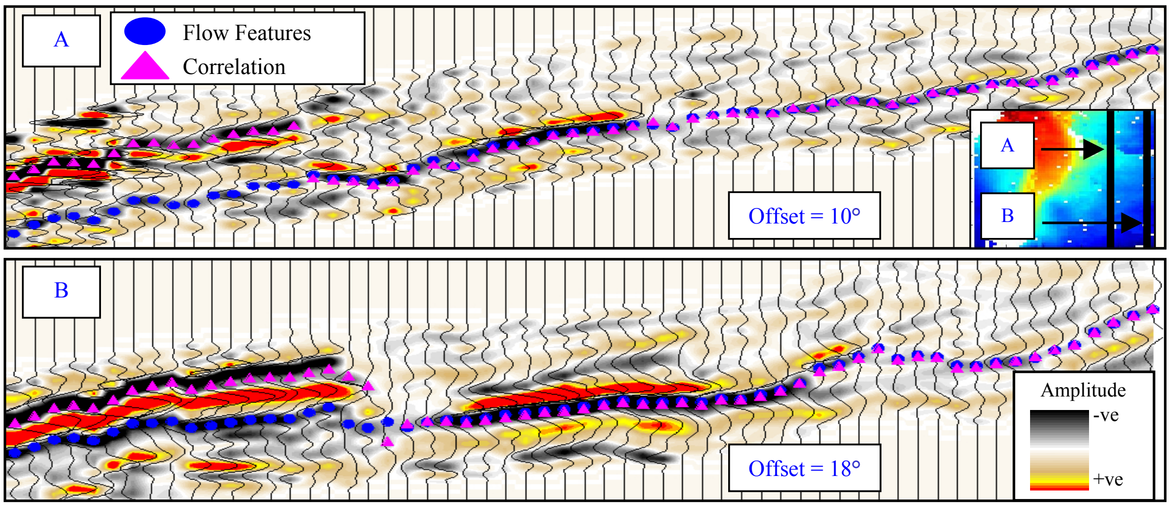

Figure 4. Comparison between hyperspace propagation using flow features and correlation autopicking results. The correlation autopicker has produced loop skipping. The 4-D constraints enforced by the propagator avoid this problem and track the event despite the varying signal-to-noise ratio.

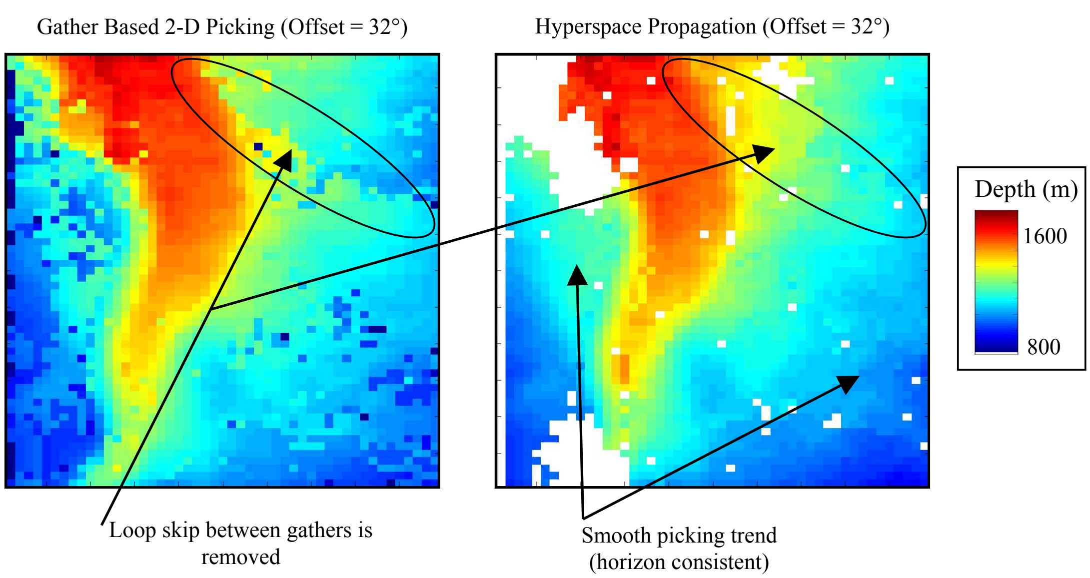

Figure 5. Comparison between 2-D gather based and hyperspace propagation autopicking results for a single offset.