Probabilistic Integration of Geomechanical and Geostatistical Inferences for Mapping Natural Fracture Networks

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1 Introduction

Estimation of a reservoir's production potential, well placement and field development depends largely on accurate modeling of the existing fracture networks. However, there is always significant uncertainty associated with the prediction of spatial location and connectivity of fracture networks due to lack of sufficient data to model them. Therefore, stochastic characterization of these fractured reservoirs becomes necessary.

Two-point statistics-based algorithms are inadequate for describing complex spatial patterns such as branching and termination of fractures described by the joint variability at multiple locations at a time [7]. Constraining the models to multiple point statistics (MPS) is necessary for producing maps that are able to accurately predict termination and intersection of the fractures without having to separate the fracture sets on the basis of their chronological evolution that may be difficult due to sparse data [5, 7]. In general, MPS is fast and robust, and superior to the traditional two point statistics while realistically reproducing the complex curvilinear geologic structures as well as integrating different data sets [6]. Conventional MPS algorithms depend on a well-defined spatial template to capture multi-scale features. Gridded domains are inefficient and tend to interrupt the spatial connectivity of the fractures. The ideas of non-gridded TIs, templates and simulated images put forth by Erzeybek (2012) are extended in a fast, robust and easily scalable MPS algorithm that utilizes self-adjusting and automatic template selection based on the configuration of conditioning data around the simulated node [1]. At the initial stages of modeling, the template identifies the coarse scale pattern and as the modeling progresses, patterns over fine and finer scales are reproduced.

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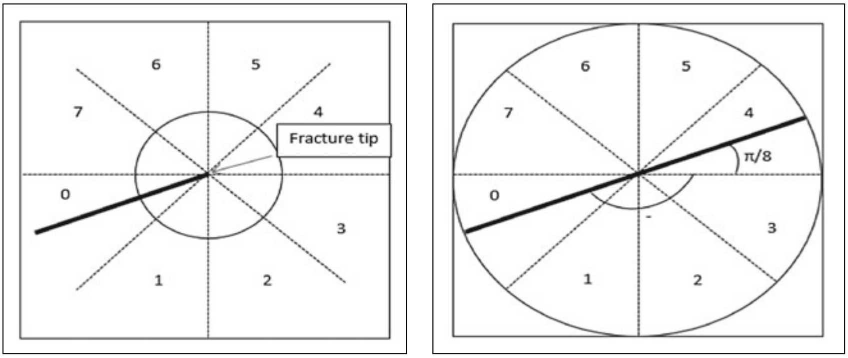
Geomechanical modeling of fractures is another widely popular approach to map fracture networks constrained to the physics of the reservoir such as far field stress conditions, presence of faults and other geological structures and local stress effects of nearby fractures. However, development of full reservoir scale physics model involving material heterogeneities beyond a length scale of 1 km involves extensive computation costs and time. It is also imperative that the uncertainties in reservoir parameters are accounted for in the prediction of reservoir performance [5]. Inferring geomechanical rules for fracture propagation in a probabilistic sense is necessary to represent the uncertainty. This is achieved using Machine Learning (ML) approaches trained on high-fidelity small scale FDEM models that predict fracture propagation pathways given a set of physics-based parameters [2].

A statistics based approach does not consider the physical processes guiding fracture propagation and a geomechanics based approach may not honor the fracture statistics observed from other auxiliary sources such as outcrop images. Therefore, amalgamation of the MPS and geomechanics based approaches is ideal for producing fracture networks, constrained to both reservoir physics and reservoir statistics. This research presents a paradigm for integration of information obtained from a stochastic simulation algorithm and geomechanics based algorithm using the Tau model proposed by Journel [4] that utilizes the concept of permanence of ratios.

2 MPS Algorithm in Classification Framework

A new and improved stochastic simulation technique based on MPS presented by Chandna (2019) is shown to improve upon the shortcomings of the classical MPS algorithms [1]. It is able to generate the desired fracture patterns without relying on any grid, either for the template or simulated image. This algorithm employs self-manipulating templates to include the specified maximum number of nodes in the vicinity of the simulation node, thereby eliminating the need to predefine templates based on visual observation and initial analysis of the training image (TI) that generally fail to capture either the small or the large-scale features unless multi-grid simulations are performed. It also circumvents calculating multiple point histograms since the algorithm operates on the principle of direct sampling [3]. In direct sampling, the pattern identified using the data configuration around the simulation node (rather than using a fixed spatial template) is searched in the TI and corresponding to the first instance of a match, the outcome at the simulation location in the TI is directly extracted and applied to the simulation. This results in more computational efficiency as the entire TI need not be searched for the calculation of the number of occurrences of the desired pattern.

The ML based geomechanical simulation algorithm outputs probabilities of the propagation of a fracture tip in each of 8 angles classes formulated by dividing the circular region around the fracture tip in 8 equal sectors of angle $\pi/4$ centered at the fracture tip (Fig. 1a). But the MPS algorithm presented by Chandna [1] is regression based and outputs discrete angles of propagation for each simulated fracture tip. For



(a) A propagating fracture

(b) An existing fracture in a TI showing conjugate angle classes (for example class 0 and 4)

Fig. 1 Angle classes 0–7, around a fracture denoted by a thick black line [2]

integrating the probability obtained from geomechanical modeling and that from MPS simulation, multiple angles of propagation are simulated for the same fracture tip, which can be binned together in these angle classes and their counts can be used to estimate the probability of simulation of each angle class. The first modification made to the algorithm constitutes outputting probabilities of angle classes of propagation for the node being simulated ($P(\theta_i)$ where i can range from 0 to 7) instead of discrete angles. Since, the MPS algorithm is based on direct sampling of the propagation angle from the TI, one option is to sample the same TI multiple times using the same template pattern to obtain multiple propagation angle classes. Each propagation angle could be different due to random order of simulation of initial flaws. These propagation angles can then be used to calculate the probability of observing a particular angle class. This can be represented as:

$$P(\theta_i) = \frac{Number\ of\ times\ \theta_i\ is\ sampled\ from\ the\ TI}{Total\ number\ of\ TI\ samplings} \tag{1}$$

A better option would be to sample multiple TIs using the same template to account for the uncertainty in the TI itself i.e.:

$$P(\theta_i) = \frac{Number\ of\ TIs\ from\ which\ \theta_i\ is\ sampled}{Total\ number\ of\ TIs} \tag{2}$$

The second approach is adopted in this research.

3 Combination of Probabilities

The combination of contributions of data events B and C from different sources to predict the probability of a desired event A is one of the most common issues faced in data sciences and most importantly in earth sciences. This conditional probability of an unknown event A occurring given two data events B and C from different sources can be expressed as $P(A|B, C)$. Commonly, this conditional probability is estimated assuming some level of independence of the data events B and C. However, such an assumption leads to non-robust algorithms with questionable prediction accuracy. Journel (2002) proposed an alternate probability integration paradigm based on the permanence of ratios which assumes that the relative contribution of any one data event to the occurrence of an outcome is independent of the relative contributions of all other data events [4]. This integration algorithm is used in the current research as a means to combine probabilities of simulated angle classes generated from the two sources: the MPS algorithm and the geomechanical simulation algorithm. The underlying assumptions of the probability integration algorithm are that the prior probability of the outcome data event ($P(A)$) and the probability of the outcome data event given the source data event for each of the source data event, ($P(A|B)$ and $P(A|C)$) can be evaluated. The permanence of ratio hypothesis breaks down the information from each source but recombines these elemental probabilities using a tau (τ) parameter(s). The tau parameters actually explore the redundancy between different data.

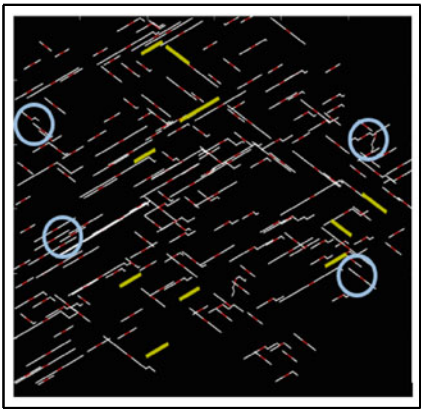
For every step of propagation of a fracture tip, probabilities of propagation along all angle classes 0 to 7 are obtained from two different sources: MPS based algorithm (Sect. 3) and geomechanics based algorithm (Sect. 2). Let $P(\theta)$ be the probability of the data event: simulation of angle class θ_i where i ranges from 0 to 7. Let $P(\theta_i|B)$ be the probability of simulation of angle class θ_i obtained from the MPS simulation and $P(\theta_i|C)$ be the probability of angle class θ_i obtained from geomechanical simulation. The desired probability of occurrence of angle class θ_i given the probabilities of its joint occurrence from the MPS and geomechanical simulations, $P(\theta_i|B, C)$ can then be evaluated using the concept of permanence of ratios:

$$P(\theta|B, C) = \frac{1}{1 + b(\frac{c}{a})^{\tau}} \tag{3}$$

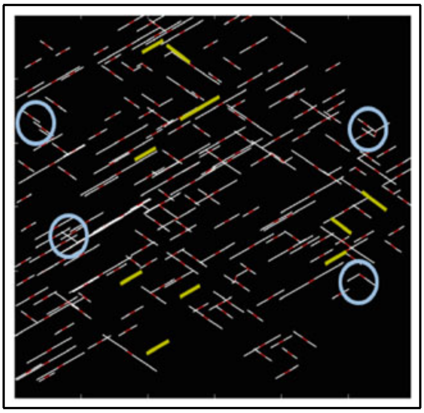
$$a = \frac{1 - P(\theta)}{P(\theta)} = \frac{P(\tilde{\theta})}{P(\theta)} \in [0, +\infty] \tag{4}$$

$$b = \frac{1 - P(\theta|B)}{P(\theta|B)} = \frac{P(\tilde{\theta}|B)}{P(\theta|B)} \in [0, +\infty] \tag{5}$$

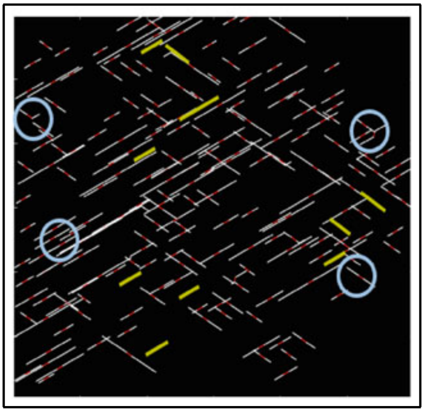
$$c = \frac{1 - P(\theta|C)}{P(\theta|C)} = \frac{P(\tilde{\theta}|C)}{P(\theta|C)} \in [0, +\infty] \tag{6}$$



(a) Simulated image using geomechanics algorithm



(b) Simulated image using MPS algorithm



(c) Simulated image using integration algorithm

Fig. 2 Comparison of final simulated images using the geomechanics, MPS and integration algorithms. Blue circles indicate highlighted areas of interest.

The contribution of data event C is manipulated and tuned using the τ parameter. For $\tau = 0$, the contribution of data event C is completely ignored and the contribution is increased or decreased depending on if $\tau > 1$ or < 1 respectively.

For demonstrating the model for integration of probabilities obtained from MPS in classification framework and reduced order machine learning based geomechanical simulation model, for propagation of every node, the integrated probability distribution over the angle classes is obtained and the node is propagated in the direction of the angle class with maximum probability of occurrence. The prior uncertainty $P(\theta)$ that results in the ratio a over angle class θ_i is assumed to be uniform and is updated based on the incremental contribution from the MPS and geomechanical simulation algorithm.

Figure 2 shows a comparison of the final simulated fracture maps generated using the geomechanics, the MPS and the integration algorithm. τ is assumed to be 1 for this simulation, implying that the relative contributions of the MPS and geomechanics algorithm to the knowledge of final predicted propagation angle, are assumed to be independent of each other. Few areas are highlighted by blue circles that show the effect of the integration algorithm on the simulated fracture maps after combining information from the two individual sources: MPS and geomechanics. Most of these correspond to hooking like pattern of the fractures. In three of the highlighted areas, statistics derived from the TIs by the MPS algorithm facilitate hooking of the fractures. However, due to the stress regimes developed around these fractures, the geomechanics algorithm predicts propagation of these fractures without any hooking with a high probability. After combining the probabilities over all possible angle classes that can be simulated, the integration algorithm simulated an angle propagation class that did not favor hooking of the fractures. Similarly, in one of the highlighted areas, hooking is favored by the integration algorithm due to a stress regime caused by possibly significant fracture interactions. In general, due to the coarse angle classes used in geomechanical simulation, a number of kinks are observed in geomechanically simulated fractures. These kinks arise as fractures tend to merge or diverge from other fractures according to the progressively changing stress states around propagating fracture tips. However, if such phenomena is not observed in the TIs, the MPS algorithm does not simulate these features. It then depends on the incremental contribution of the MPS and the geomechanical information to the knowledge of the final predicted propagation angle class to determine if such features would be observed in the final simulated images. In this case, such features are not simulated by the integration algorithm due to lower contribution of the geomechanics algorithm towards generation of propagation angle classes that may describe the development of these features.

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