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A methodology for the characterization of flow conductivity through the identification of communities in samples of fractured rocks

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ABSTRACT

We present a methodology that characterizes through the topology of a network the capability of flow conductivity in fractures associated to a reservoir under study. This strategy considers the fracture image as a graph, and is focused on two key aspects. The first is to identify communities or sets of nodes that are more conductive, and the second one is to find nodes that form the largest paths and have therefore more possibility of serving as flow channels. The methodology is divided into two stages, the first stage obtains the cross points from fracture networks. The second stage deepens on the community identification. This second stage carries out the process of identifying conductive nodes by using centrality measures (betweenness, eccentricity and closeness) for evaluating each node in the network. Then an optimization modularity method is applied in order to form communities using two different types of weights between cross points or nodes. Finally, each community is associated with the average value of each measure. In this way the maximum values in betweenness and eccentricity are selected for identifying communities with the most important nodes in the network. The results obtained allow us to show regions in the fracture network that are more conductive according to the topology. In addition, this general methodology can be applied to other fracture characteristics.

1. Introduction

Many real world problems such as biological, social, metabolic, food, neural networks and pathological networks among others can be modeled and studied as complex networks (Kolaczyk, 2009; Cohen, & Havlin, 2010; Estrada, 2011). They are mathematically represented and topologically studied to uncover some structural properties. In the petroleum industry one issue of importance is the study and analysis of fluid flow in fractured rocks. In this paper we present a methodology for the characterization, through the topology of a network, of the capability of flow conductivity in fractures associated to a reservoir under study. Our methodology extracts from a fracture image a graph focusing on two key aspects. The first is to identify regions of fractures that are more conductive, and the second one is to find nodes that belong to the largest paths that have more possibility of serving as flow channels. This paper deals with real fracture networks derived from original hand-sample images. These images of rocks correspond to a Gulf of Mexico oil reservoir, and are used as test examples for identifying properties related to the fluid flow from a topological perspective. This methodology assumes that the fractures in the image have all being identified as conductive. Then it determines qualitatively different conductive regions in the fracture network through the analysis of the cross points of the fractures, and quantifies the connectivity among these cross points and their topological function within the network. This methodology consists of: (i) the application of centrality measures that involves the estimation of shortest paths, and (ii) the identification of node sets by means of community detection. The communities are subunits associated with the more highly interconnected parts used for determining the global organization in the network (Lancichinetti, Kivelä, Saramäki, Fortunato, 2010). Many methods have been developed for the identification of communities (Clauset, Newman, & Moore, 2004; Girvan & Newman, 2002; Newman, 2004; Porter, Onnela, & Mucha, 2009; Radicchi, Castellano, Cecconi, Loreto, & Parisi, 2004). We apply an efficient method reported in the literature (Condon & Karp, 2001; Lancichinetti & Fortunato, 2009) for grouping sets of nodes based on a modularity function. In addition, for the construction of these communities a formulation for computing the weights among cross points is proposed. This approach will help in analyzing different study regions and to characterize the fracture networks by means of the topological properties obtained, and hence it can identify conductive regions. Also these results can be used in combination with other geophysical or petrophysical properties from the fracture network.

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The paper is organized as follows. In Section 2, previous work and basic concepts are described; in particular the centrality measures and a method for determining communities or regions are discussed. In Section 3, our general scheme is explained. In this part the association between the centrality measures and the identification of communities are described. In Section 4, we show our results, applying the methodology to fracture hand-sample images. Finally, in Section 5, we give our conclusions.

2. Previous works and theoretical framework

In the characterization of naturally fractured reservoirs (NFR) one of the main challenges in the hydrocarbon industry is the generation of a representative model for it (Aguilera, 1995; Baker & Kuppe, 2000; Narr, Schechter, & Thompson, 2006; Nelson, 2001; Nikravesh, 2004). This characterization requires putting together different data sources about the whole reservoir (Bogatkov & Babadagli, 2007; Gauthier, Garcia, & Daniel, 2002; Guerreiro, Silva, Alcobia, & Soares, 2000). One of the important problems is the determination of the nature, and disposition of heterogeneities that inevitably occur in petroliferous formations in order to predict the capability for fluid transport. Different strategies have been developed to tackle this problem. Some authors have focused on the analysis of the properties of the fluid flow (Sarda, Jeannin, Basquet, & Bourbiaux, 2002; Warren & Price, 1961; Yang, Myer, Brown, & Cook, 1995), others in the modeling and simulation of fracture networks (Berkowitz, 2002; Sarkar, Toksöz, & Burns, 2004), and some others in the analysis of topological properties by applying statistical techniques on the structure where the fluid transport may occur (Cacas, Ledoux, de Marsily, & Tillie, 1990), using in most cases synthetically generated fracture networks (Ghaffar, Nasseri, & Young, 2012). In this work, a topological approach on fracture rocks is presented by transforming and analyzing the fracture network from an original fracture image. This network is then analyzed as a complex network. It must be pointed out that a large majority of complex networks come from problems in the areas of biology, communication, internet, and social sciences (Girvan & Newman, 2002; Newman 2004; Subelj, Furlan, & Bajec, 2011). In geology this point of view is new to the best of our knowledge although many developments have been implemented for images associated to different types of data such as gamma ray records (Fiorini, Abel, & Scherer, 2011; Ya-Hao, 2008). A first attempt to the analysis of fracture systems as complex networks can be consulted in Santiago, Romero-Salcedo, and Velasco-Hernández, (2012). The analysis involves a technique that allows the classification of a set of images into two groups and the identification of the distributions of intersection points of the segments of fractures. In the present work a technique for identifying communities or regions is included. In reservoir characterization, some traditional clustering techniques have been used as, for example, k-means, neural network and fuzzy c-means clustering for identifying sets of elements with common properties (Liu, 2012; Nikravesh, 2004). The latter applies a clustering technique on a specific network structure for information sharing and diffusion of information and to examine the network content. A group of nodes is defined in the complex network terminology as a community (Fortunato, 2010; Newman, 2010). One of the earlier methods for detecting communities is the hierarchical divisive algorithm proposed by Girvan and Newman (2002). The idea is to remove iteratively links based on the value of their betweenness (this measure is described later). The procedure ends when the resulting partition reaches a maximum limit. One variation of this method is to use the edge clustering coefficient (Radicchi et al., 2004). The fast greedy modularity optimization proposed in Clauset et al. (2004) is a fast algorithm derived from a previous work of Newman (2004). The process begins from a set of isolated nodes where the links are iteratively added until generating a maximum number of communities obtained by the method of Girvan and Newman (2002) in each step. One method derived from it is the exhaustive modularity optimization via simulated annealing. Fast modularity optimization defined by Blondel, Guillame Jean-Loup, and Lefebvre (2008), is a multistep method based on the local optimization of modularity (Girvan & Newman, 2002) in the neighborhood of each node. In our work this technique for grouping nodes is applied because of its computational efficiency. Other methods focus on determining overlapping of nodes (Palla, Derényi, Farkas, & Vicsek, 2005), to find the best cluster structure of a graph (Rosvall & Bergstrom, 2008), to simulate the diffusion process on a graph (Van Dongen, 2000), or determining the spectral properties of the graph (Donetti & Muñoz, 2005).

In our methodology the analysis of the flow conductivity regions in fracture networks is executed in two main steps. First centrality measures to all the nodes are applied, and then modularity optimization (Blondel et al., 2008) is used. The formulation of a graph and its association with the fracture network is defined in the next subsections; also the methods, parameters and measures employed in the methodology are described.

2.1. Formal definition of a graph

Formally a graph is defined as $G = (V, E)$ where $V = \{v_1, v_2, \ldots, v_n\}$ is the set of nodes, and $E = \{e_1, e_2, \ldots, e_m\}$ the set of edges; n and m denote the number of nodes and edges, respectively. For an unweighted graph, the weight $\omega(e) = 1$, for all $e \in E$, and p_{st} is a path from $s \in V$ to $t \in V$ formed by a sequence of nodes and adjacent edges, beginning in the node s and ending in the node t. $d(s, t)$ is the length of a path measured by the sum of the edge weights between the nodes s and t. $d_G(s, t)$ is the geodesic path, e.g., the shortest path between two nodes, and $\sigma_{st} = \sigma_{ts}$ is the number of the shortest paths from $s \in V$ to $t \in V$.

2.2. Centrality measures

The intuitive concept of centrality based upon the structural properties of centrality of a graph G, was introduced initially by Bavelas (1948), and one of these measures is the betweenness centrality proposed by Anthonisse (1971), and latter by Freeman (1977), who define centrality $C_B(i)$ as the ratio between $\sigma_{st}(i)$ and σ_{si}, i.e., the number of times in which a node i falls on the geodesic path between the nodes s and t, and the number of shortest paths between the nodes s and t, respectively. The formula for computing betweenness of a certain node i is presented in (1). Thus, it measures the potential for controlling the communication of a network. An improved version of this centrality index is defined in Brandes (2001) and is used in this work. This improved index includes a more efficient and faster way to compute large and very sparse networks. It is based on an accumulation technique that solves the single-source shortest-path problem by using the Bellman criterion, where $\sigma_{st}(i)$ takes the value of $\sigma_{si} \cdot \sigma_{it}$ if the shortest paths between s and t pass through i, otherwise takes zero as is shown in (2). In this expression, $d_G(s, t)$ is the shortest distance between the nodes s and t. A high centrality score indicates that a node can be reached by other nodes on short paths. In this work, this measure is applied to all the cross points of each fracture image, and the maximum scores obtained indicate the community of nodes with more capability for distributing any fluid in the fracture system.

$$C_B(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}, \quad \forall s, t \in V \tag{1}$$

$$\sigma_{st}(i) = \begin{cases} 0 & \text{if } d_G(s,t) < d_G(s,i) + d_G(i,t) \\ \sigma_{si} \cdot \sigma_{it} & \text{otherwise} \end{cases} \tag{2}$$