The detailed theory of the selected DTW algorithm can be found out in (Herrera2014). In brief, DTW algorithm finds an optimal non-linear alignment between the time sequences sampled at the same sampling frequency. Linear programing while computing the DTW distance (Herrera2014) can accommodate the stretching and squeezing in the time series. DTW finds the minimum cost function for traversing from the initial point to the final point of the time sequence. Figure 4 represents the normalized outcome of DTW method on the same well-log dataset. The window parameter associated with DTW has been empirically selected as 100. However, we have observed that the outcome of DTW algorithm has not been modified largely while modulating the window parameter. In case of DTW, the output metric represents the similarity measure in a reverse manner using distance instead of similarity. For example, it can be seen from Figure 3 that the characteristics of Well 1 is not similar to the other wells. In case of Figure 4, the distance between Well 1 and the remaining wells are comparatively large. Thus, the performance of DTW algorithm has validated the performance of the Motif-Synchronization algorithm. Thus, the proposed method has been established to be an efficient similarity assessment technique involving geophysical signals. The well-log signals are high information carrying signals characterized with high frequencies (Chaki2015, Chaki2017, Chaki2018, and Chaki2019). Therefore, one important and counter-intuitive aspect of the study is the development of a robust representation based on the comparison of the high-frequency signals in constant time steps.

Conclusions

This paper proposes an association based method to obtain synchronization degree among multiple well logs. The results obtained in this paper suggests that similarity matching can be automated using the proposed motif-synchronization based method. The selection of associated parameters like the degree of a motif, time-delay, and window size are crucial to bring out inherent information from these non-linear logs. The different metrics such as correlation coefficient, distance computed by DTW algorithm and synchronization degree obtained from motif-synchronization are based on different aspects of signal processing. Therefore, the comparison between these measures is qualitative rather than quantitative.

As the similarity between different portions of well logs reflects the lithological similarity between the wells. This method would be beneficial to the geoscientists for similarity matching along with visual inspection. Instead of manually observing every well logs, it is a much simple and fast approach to calculate the similarity measures of the time sequences and inspect the similarity measure matrix at a glance. The similarity measures between the well-logs enable a user to identify well tops. In case the well tops information is available in advance, then the outcome of the similarity measures algorithms can be verified. Moreover, pseudo logs of geophysical properties can also be generated between closely connected well logs using similarity information. A comparative analysis of all recently published similarity methods like SL, VGS, and motif-synchronization etc. along with recurrence-based algorithms can be carried out using a geophysical dataset in future.

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