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Residue feature analysis with empirical mode decomposition for mining spatial sequential patterns from serial remote sensing images

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Abstract
An extensive growth of serial remote sensing images paves the way for abundant data intended for the sequential spatial pattern determination in several fields like monitoring of agriculture, development of urban areas, and the vegetative area. However, conventional spatial sequential pattern mining is not applied efficiently or directly in the aspect of serial remote sensing images. Therefore, a residue feature analysis with empirical mode decomposition is proposed so as to enhance the spatial sequential pattern mining efficacy from the raster serial remote sensing images. At first, input images are being extracted by means of minima and maxima pattern by computing the mean of envelops and the intrinsic mode function components. If the intrinsic mode function condition is satisfied, then it is being subtracted from the original image; finally, the image is decomposed into many intrinsic mode functions and residue. The experimental outcomes attained indicate that the proposed strategy is proficient of mining spatial sequential pattern from the images of serial remote sensing. Though the support values of the patterns might not be attained accurately, the presented scheme guarantees that the whole patters are being extracted at lower consumption of time.

Keywords
serial remote sensing images, intrinsic mode function (IMF), image decomposition, residue feature analysis, empirical mode decomposition (EMD)

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Анализ остаточных признаков с декомпозицией по эмпирическим модам для извлечения пространственных последовательных шаблонов из серийных изображений дистанционного зондирования

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Аннотация
Значительный рост последовательно получаемых изображений при дистанционном зондировании ведет к увеличению количества данных. Такие данные используются в таких областях как: мониторинг сельского хозяйства, развитие городских районов и наблюдение за растительными зонами. Отметим, что обычное последовательное извлечение пространственных структур эффективно не применяется особенно по отношению к последовательно получаемым изображениям в результате дистанционного зондирования. Предложен анализ

остаточных признаков при разложении изображений по эмпирическим модам для повышения эффективности извлечения пространственных последовательных структур из растровых изображений дистанционного зондирования. Входные изображения извлечены с помощью минимальных и максимальных растровых структур путем вычисления среднего значения огибающих и компонентов функции разложения на внутренние моды для спектрального анализа Гильберта. При выполнении условия функции разложения на внутренние моды, производится операция вычитания функции из исходного изображения. Далее изображение разлагается на множество функций внутренних мод и на остаток. Полученные экспериментальные результаты показали, что предложенная стратегия способна непрерывно извлекать пространственные структуры из последовательно получаемых изображений дистанционного зондирования. Хотя опорные значения структур могут быть получены неточно, представленная схема гарантирует, что структуры в целом извлекаются с меньшими затратами времени.

Ключевые слова
последовательные изображения дистанционного зондирования, функция разложения на внутренние моды (IMF), разложение изображения, анализ остаточных признаков, разложение по эмпирическим модам (EMD)

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Introduction

A growth of technology in earth observation leads to development of spatial data accumulation continuously. Amongst this kind of data, due to its temporal and spatial features Serial Remote Sensing Images (SRSI) offer potential for tracking changes in environment, urban expansion, development of agriculture and so on. Several studies have been made that focus on the knowledge mining from the SRSI [1]. The growth of SRSI offers huge amount of data for recognizing spatial sequential patterns in several arenas [2–4]. The Sequential Spatial Pattern Mining (SSPM) is regarded as the utmost significant means of the information which was being concealed at the SRSI and, in turn, attracts huge range of interest over researchers. The scheme of Sequential Pattern Mining (SPM) is regarded to be the technical SSPM base that mostly intends in extracting the recurrent patterns from the database operation. It is varied from their precursor SSPM that tries in discovering the spatio-temporal recurrent categorizations from the geospatial databases [5, 6]. The structure complexity, geospatial data desired features like spatial auto-correlation and spatial relation amongst objects, and huge volumes, in turn, prevent the SPM algorithms from being applied effectually for the sequential spatial pattern mining. Moreover, these structure complexity, desired features, and high volumes prevent the use of SPM approach in mining effective spatial sequence pattern [7–10].

Many approaches have been presented in existing techniques. However, there were many limitations such as inefficiency in decomposing input image. So as to overcome this drawback, the proposed approach is presented by employing Empirical Mode Decomposition (EMD) method for the effective decomposition of input image.

Related work

An approach of pixel clustering was presented in [11] to enhance the SSPM from the raster SRSI. At first, the image is compressed with the use of Run-Length Coding (RLC) scheme. After that, the pixels were being clustered with the use of RLC based function of spatial overlay. Eventually, a strategy of pruning is employed for prefix span extending approach so as to skip unwanted database while skimming and mining from the groups of pixel. In this work, authors have analyzed the issues in spatial mining from SRSI and proposed prefix Span algorithms for improving the efficiency of sequential spatial mining from SRSI. The work claims that it proved the improved efficiency in spatial mining and it can be applied in various fields.

However, the accuracy of pattern recognition is low when compared to other related work.

In the paper [12], the authors presented a Quantized ternary pattern dependent grouping of pixel with the Single Value Decomposition and the RLC for pattern mining. These utilized processes were later experimented using dataset cropland data. A presented approach was effective in terms of mining time and sequence pattern generation. However, the work increases the computational time that leads to performance degradation in the mining process.

The author in this paper [13] presented spatial-spectral ConvLSTM 3-D version for preserving the inherent hyperspectral data structure to enhance the performance of classification. The conducted experiments in three common employed Histopathological Image Classification (HIS) datasets, illustrate that the presented models have some competitive benefits and might help in offering good classification performance compared to other traditional systems. However, it is not evident that the proposed work alone provides a better classification. The proposed work should be combined with other modern models to yield a better result.

A novel Frequent Pattern Mining was suggested in [14] which was called Mining Frequent Patterns (MFP) and had two central characteristics that were new. The attained outcome describes that the MFP approach is effective in recognizing the patterns in the optimized time. Even though the work reduces the time in processing the pattern during classification, the feature selection approach utilized in the work is not efficient in terms of accuracy.

The Remote Sensing Image (RSI) classification is regarded as a normal employment of RSI [15]. For enhancing the performance of RSI classifier, groupings of the multiplier classifiers were utilized to categorize images in Landsat-8 OLI (Landsat-8 Operational Land Imager). Few combinations of classifier techniques and algorithms are evaluated. This approach uses a voting-based classification technique utilizing ensemble learning to improve the accuracy of classification. Even though this method achieves higher accuracy, the work caused stability issues due to the use of multiple classifiers.

A survey was carried out in [16] regarding the mining sequential pattern and its applications. The aim was to offer an introduction and also the SPM with the recent research and advances opportunities survey. The approach was divided into four major portions: initially, SPM was defined by reviewing their application after that. The terminologies and the major aspects were introduced. However, the major strategies and approaches were projected for solving SPM.

A well-defined final research process in the form of images retrieval based on quantization, called hypergraph and hacking process, was introduced in [17]. In [18], the author employed encoders that are bi-generative, along with the multi-modal stochastic Recurrent Neural Network intended for effective image recovery, and binary auto-encoders that are hierarchical.

An algorithm of sparse Support Vector Machine (SVM) classifier was presented in the paper[19]. The segmented images were then categorized as a small number of patches. After the process of extraction, segmentation of images was made and was then categorized to small patches.

The Modified Extrema Pattern is used to provide grey-scale invariant transformation of pixel intensity values [20]. An improved Single Shot Detector model was established for detecting an object over remote sensing photos or images [21]. A contourlet transform was employed in for identifying the directions according to the strategy as this helps to effectively present images as multiple directional bands that havemore accurate directional information than the spatial derivatives [22].

From the literatures studied, we observed that all the approaches tried to satisfy the efficient pattern mining from rater images. Most of the work discussed in this section is related to the calculation of individual pixel which is unnecessary and will result in additional overhead in computational process. In our work, we proposed an idea of grouping the pixels that are having similar patterns. Then we perform calculating the grouped pixel which reduces the computational time.

Proposed work

The entire workflow of the presented technique is illustrated briefly in this part. The workflow depiction is provided in Fig. 1.

Maxima and minima should be computed first for the data decomposing into Intrinsic Mode Functions (IMFs). To find the maxima and minima, you have to locate the points where slope changes occurred. After finding these points, one spline curve for each is placed for maxima and minima. These curves define the upper and lower envelopes. Having these, mean of the envelope is computed. The calculation for the mean envelope is given in the following formula

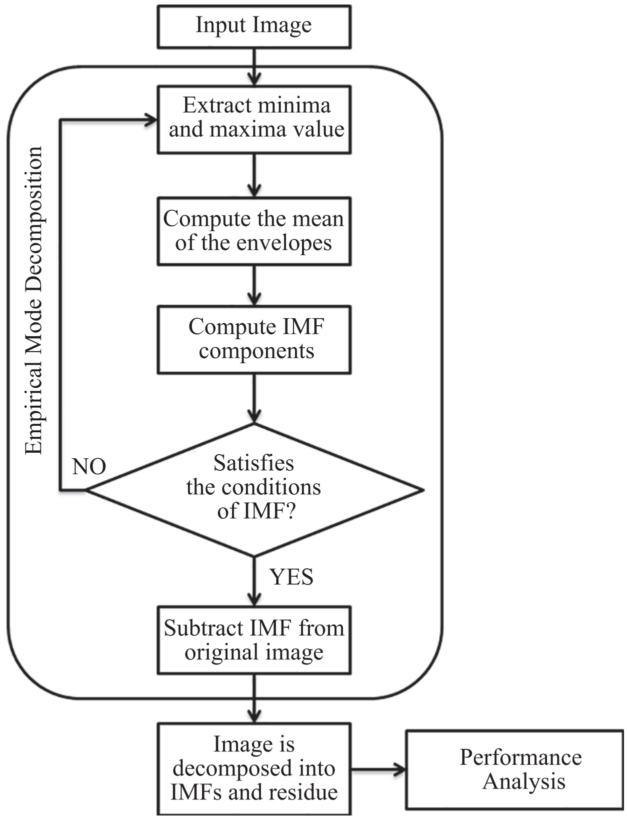

Fig. 1. Workflow of presented scheme

$$m_e = e_{up} + e_{lower}/2,$$

where e_{up}, e_{lower} are the upper and lower envelope respectively.

Then the mean envelope m_e is subtracted from the signal $d(t)$ to generate the first envelope

$$I_1 = d(t) - m_e,$$

where I_1 is the first IMF, $d(t)$ is the signal and m_e is the mean envelope. The outcome of the above equation is the first component of the data. This process is repeated and finally sum of IMFs and residue signal is generated. The steps for the process are given in EMD for image decomposition.

Input image retrieval, processing and decomposition

The work flow diagram is shown above. Initially, input images are taken and a difference is being estimated among the adjacent and the center pixel of every pattern over the estimation of number of columns and rows. Then the extraction of minima and maxima values is made from the image. The conversion of binary patterns is made with regard to the center pixel based on the upper and lower envelops. Then we compute the mean of this envelop. At the center pixel, an extrema patterns are formed by means of IMF which is then followed by the Hilbert transformation process of that specified pattern. This IMF needs to be satisfied so that the properties of the input image should be preserved. Thus, a decomposition process is carried out to decompose the image as IMFs and residue.

Empirical Mode Decomposition for image decomposition

We proposed an enhanced Prefix span model called EMD prefix span. The proposed model is regarded as the image decomposition depending on the image local characteristics that fascinates the multi-resolution advantages of the wavelet transform and thus overwhelms the problem of selecting the basis of wavelet thereby determining the scale of decomposition in the wavelet transform. Hence, it is highly appropriate for the non-stationary non-linear image analysis and is thus adaptive EMD. The EMD considers that any complex image is comprised of IMFs that are simple ones, and each IMF is independent mutually. This EMD could be decomposed as different scales, or time series data trends, into their step-by-step component with an image sequence series having similar characteristics of scale produced. By this, the non-linear non-stationary data is being transformed as a smooth linear data. On comparing the original sequence of data, after decomposition the sequence have greater regularity which helps in recognizing hidden relationship and might enhance the prediction accuracy. The EMD steps for the given time series are shown below.

Step 1: the upper envelope $e_{up}(t)$ and the lower envelop $e_{lower}(t)$ are determined from the local minimum and local maximum of time series data $x(t)$, and, in turn, computes the mean envelope $m_1(t)$.

$$m_1(t) = \frac{e_{up}(t) + e_{lower}(t)}{2}.$$

Step 2: subtract $m_1(t)$ from the $x(t)$ for getting $h_1(t)$ as the lower image $x(t)$; step 1 is repeated on taking screening k times till $h_1(t) = x(t) - m_1(t)$ meets the conditions of IMF; after that $c_1(t)$ is regraded as the initial IMF time series component since it comprises of the shorter periodic component of the original sequence.

$$c_1(t) = x(t) - m_1(t).$$

Step 3: once the first IMF component is separated from time series $x(t)$, the other components $r_1(t)$ of $x(t)$ is attained as shown:

$$r_1(t) = x(t) - c_1(t).$$

Step 4: consider $r_1(t)$ as the new time series, and the steps 1 and 3 are repeated for attaining the qualified IMF component series $c_1(t)$ and the residual $r_n(t)$. After that, the original time series $x(t)$ is expressed by means of the following IMF component and the residual component as shown:

$$x(t) = \sum_{n=1}^{n} c_i(t) + r_n(t).$$

Of these steps from 1 to 4, the original time series is decomposed as sub-sequences of varied frequencies termed IMF and residual r. After that, the prediction trend of all sequence is being made and the outcomes of subsequence prediction are being superimposed for attaining the original sequence prediction outcome.

Step 5: the noise-added image $s_j(t)$ is decomposed as n IMFs and the residues by means of

$$s_j(t) = \sum_{i=1}^{n} c_{ij}(t) + r_j(t).$$

Here, $c_{ij}(t)$ and $r_j(t)$ signifies i-th IMF and the residues of j-th realization correspondingly.

Step 6: the ensemble mean is computed as shown:

$$c_i(t) = \frac{1}{M}\sum_{j=1}^{M} c_{ij}(t),$$

$$r(t) = \frac{1}{M}\sum_{j=1}^{M} r_j(t).$$

Here, $c_i(t)$ signifies the EMD's IMF and $r(t)$ illustrates the EMD residues.

Performance Analysis

The assessment of projected approach performance is made and the outcomes attained are shown in this section. The Cropland data layer dataset is utilized so as to estimate the overall performance of proposed algorithm. From the following link[1], the dataset is obtained.

The images that consist of continental areas of the US, termed Iowa state. It contains about 150 K sq.kms, where each pixel of the image comprises about sq.m. The several cultivated yields at areas are recognized by map color. This datasets were segregated as 4 categories such as D1, D2, D3, and D4 based on the period of time in image required.

Fig. 2, *a* shows the representation of input image. The input image attained from the dataset is projected below in Fig. 2, *a*. The input image is taken from cropland layer dataset. It represents the area Iowa state of US. The colors on the map represent the different crops cultivated in that region.

[1] https://nassgeodata.gmu.edu/CropScape/ (accessed: 11.11.2021).

Table 1. Dataset detail representation. Duration from 2010 to 2016 year

ID of the dataset	Region	Volume of data, MB	Pixel count
D1	Butler country smaller portion	1.7	21 × 132
D2	Butler country Regions	20	1323 × 3534
D3	ASD 1910 Region	141	5971 × 3534
D4	IOWA state Region	594	17795 × 11671

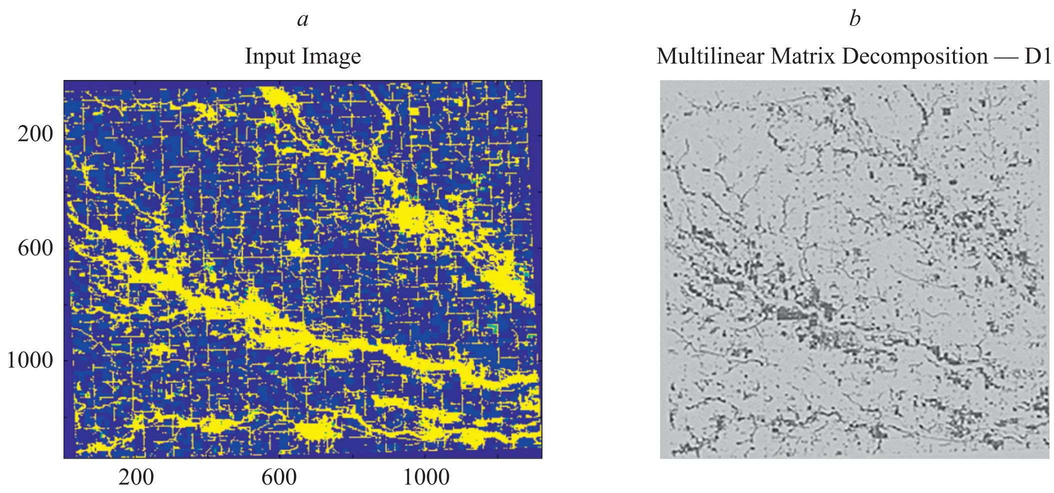

Fig. 2. Images of 1200 × 1200 pixels: input (*a*) and disassembled (decomposition of a multilinear matrix — D1) (*b*)

Fig. 2, *b* signifies the decomposed image. The attained decomposed image is represented. The decomposition is carried out by means of EMD.

The consumption of time analysis on the test D1, D2, D3, and D4 datasets is represented in Fig 3.

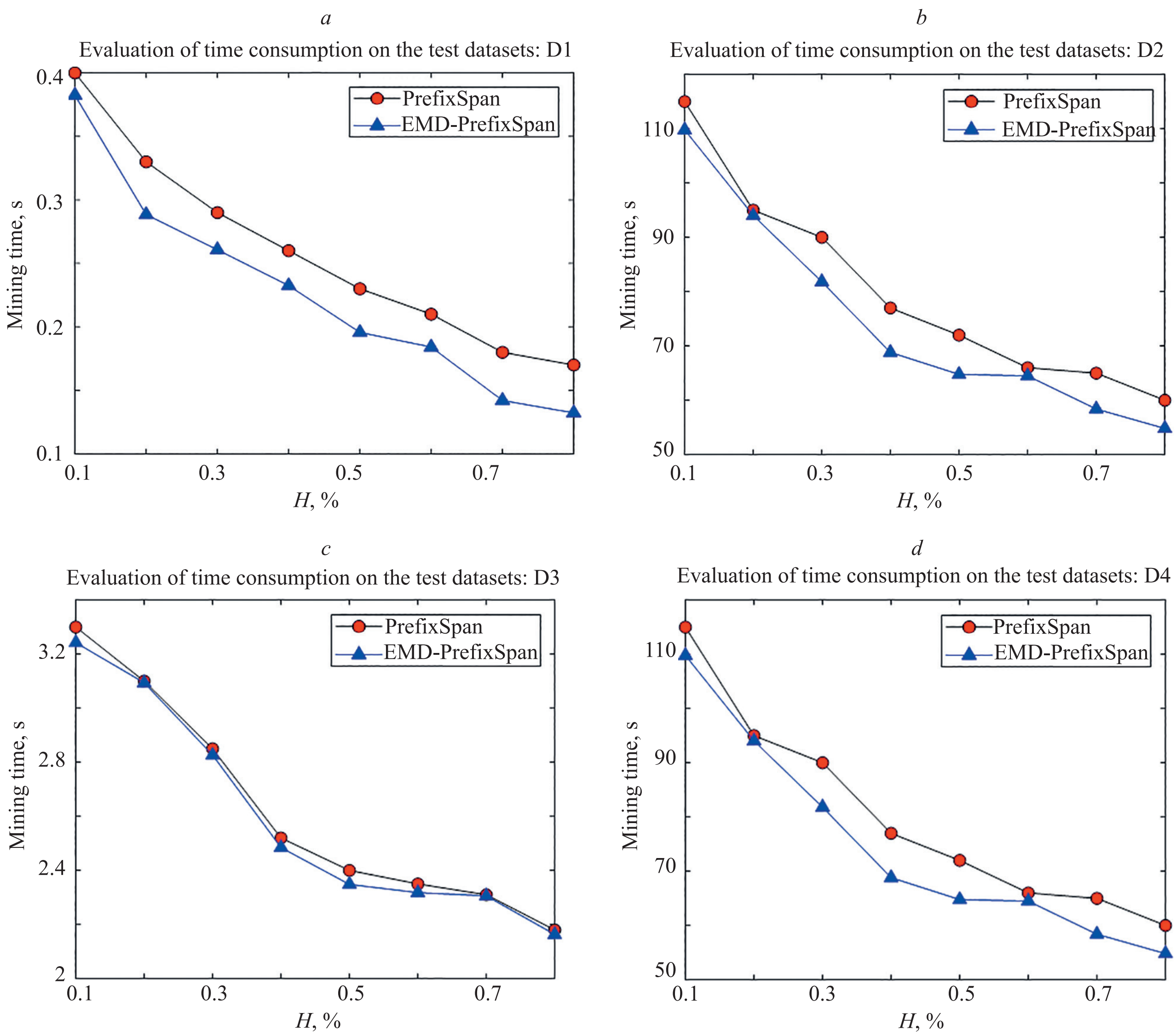

Fig. 3. Analysis of time consumption by a set of test data: D1 (*a*); D2 (*b*); D3 (*c*); D4 (*d*)

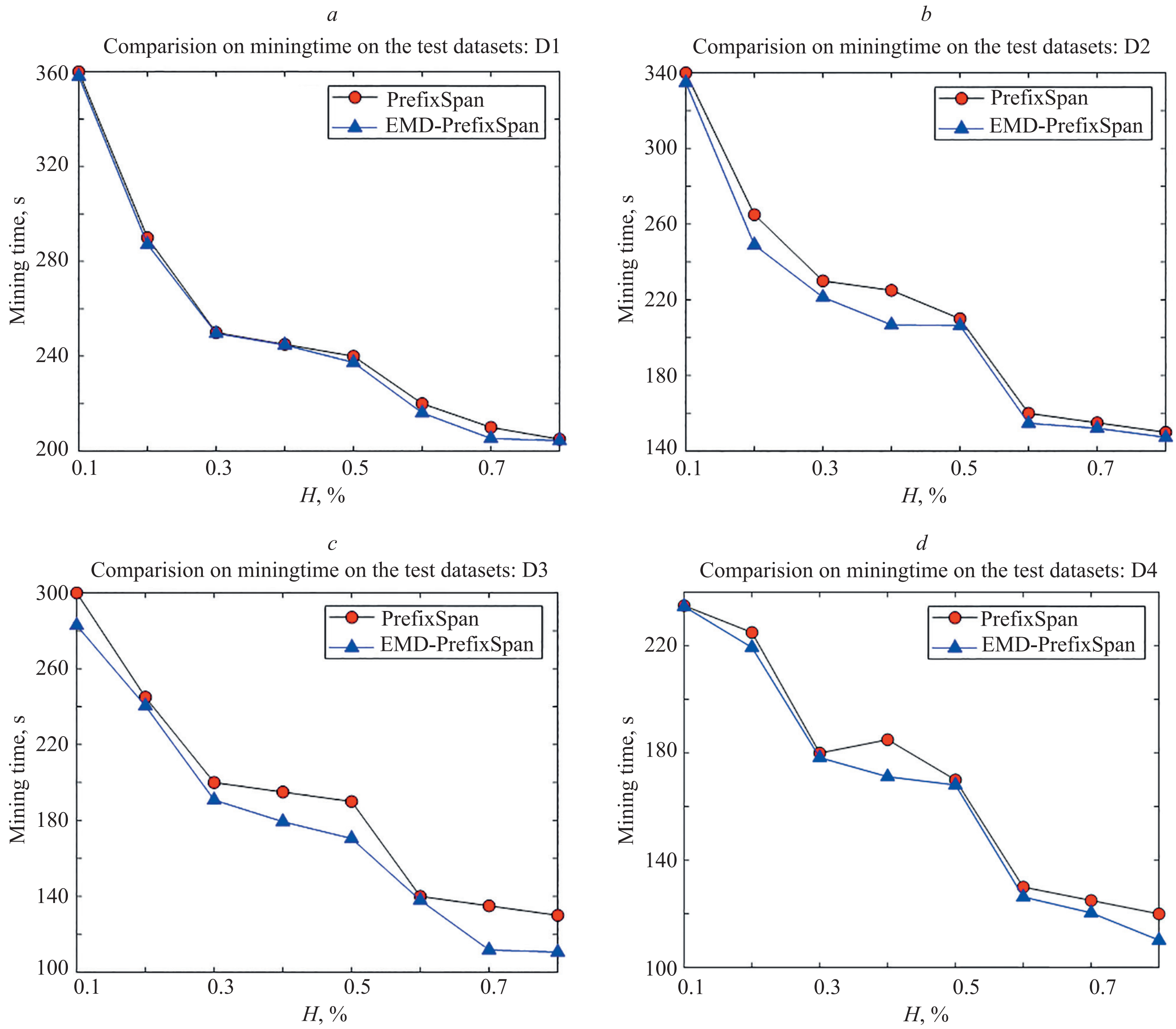

Fig. 4. Comparative estimation test datasets mining time: D1 (*a*); D2 (*b*); D3 (*c*); D4 (*d*)

H represents the user defined threshold value which is the number of occurrences of a frequent sequence. The mining time is decreased when the threshold value increases. The analysis was carried and an outcome is thus related to the traditional approaches for proving the proposed system efficiency of presented technique. The estimation of mining time on D1, D2, D3, and D4 test dataset is projected in Fig. 4. The estimation is carried and an outcome attained is then related to traditional approaches for proving the efficiency of presented method with other existing methodology. The outcomes show that the projected system is effectual in overwhelming the traditional issues in SRSI images.

Fig. 5 shows the comparative analysis of support produced by prefix span model and the EMD-Prefix span model. Support values indicate the sequence of minimum number of patterns that appears frequently in the mining process. The support values are counted by the number of times the dataset been mined to get the accurate results. X-axis units are simple sequential numbers. From the above comparative analysis, support generated by the EMD-Prefix range is minimal when compared to the Prefix range model. The assessment of support values of the SPM approach with traditional approaches is made and the outcome attained is shown in Fig. 5. Therefore, through the entire performance

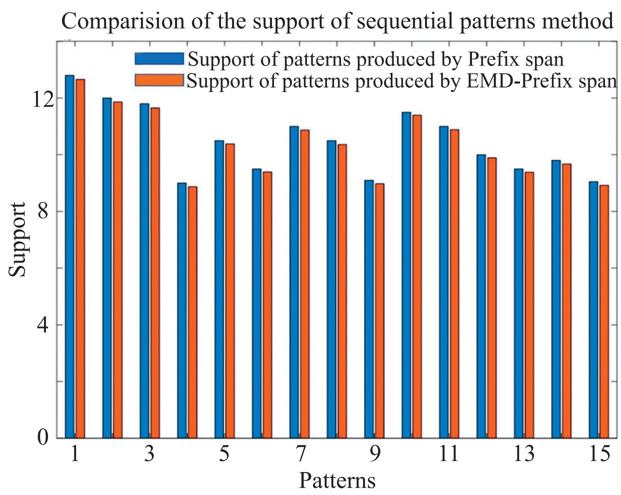

Fig. 5. Comparative analysis of SPM method support values

examination, it was obvious that the projected scheme is improved by the offering decreased rate of mining time and reducing the consumption time for the test datasets.

Conclusion

An effective approach of residue feature analysis with empirical mode decomposition was presented for enhancing the competence of SSPM from raster SRSI. Initially, images were extracted through minima and maxima patterns by computing the mean of envelops and the IMF components. In case if the IMF condition is satisfied, the IMF is subtracted from original image and then the image was decomposed into IMFs and residue.

The technique proposed in this article can effectively decompose the image and thus help to correctly extract SSP from SRSI. Though, for the patterns the support rates might not be attained precisely, the projected technique may perhaps guarantee that entire patterns were being mined at lower time consumption.

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