# ON THE USE OF TIME-FREQUENCY FEATURES FOR DETECTING AND CLASSIFYING EPILEPTIC SEIZURE ACTIVITIES IN NON-STATIONARY EEG SIGNALS

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## ABSTRACT

This paper proposes new time-frequency features for detecting and classifying epileptic seizure activities in non-stationary EEG signals. These features are obtained by translating and combining the most relevant time-domain and frequency-domain features into a joint time-frequency domain in order to improve the performance of EEG seizure detection and classification of non-stationary EEG signals. The optimal relevant translated features are selected according maximum relevance and minimum redundancy criteria. The experiment results obtained on real EEG data, show that the use of the translated and the selected relevant time-frequency features improves significantly the EEG classification results compared against the use of both original time-domain and frequency-domain features.

***Index Terms***— Biomedical signal processing, time-frequency representation, time-frequency features extraction, Epileptic seizure detection, EEG classification.

## 1. INTRODUCTION: PROBLEMATIC, CONTEXT AND RELATED WORK

Electroencephalogram (EEG) is a representative signal containing information of the electrical activity of the brain generated by the cerebral cortex nerve cells; it has been the most utilized signal to detect different abnormalities such as seizure which can lead to permanent brain damage and even fatalities if not detected and treated early [1]. Analyzing the EEG is a proven approach for detecting seizure but their manual detection is time consuming especially with long recordings. It is therefore desired to develop an automated system which can help the neurophysiologists to detect the EEG seizure in the brain with high accuracy and then to determinate the appropriate diagnostic. The EEG signal parameters extracted and analyzed using computer based digital signal and image processing techniques are highly useful and more suitable for detecting EEG seizure activities and classifying them with a relevant degree of severity in such system [2, 3, 4, 5]. A typical scheme for an EEG seizure detection and classification system includes the following three steps: (1) EEG signal analysis in either time, frequency, time-scale or joint time-frequency (T-F) domain, (2) features selection and extraction which characterize the seizure activity, and (3) classification of these features in order to detect the presence of seizure activity in the EEG signal by assigning it to seizure abnormality class or normal class.

Various methods for detecting EEG seizure have been previously proposed based on the above-mentioned scheme. These methods use EEG features in the time domain [6, 7, 8, 9], frequency domain [7, 8], and T-F domain [3, 4, 5], as well as time-scale domain [10]. The time-domain features extracted from EEG signals include: statistical moments-based (e.g. central moments and coefficient of variation), amplitude-based (e.g. average amplitude and derivatives of the signal's amplitude), and entropy-based (e.g. Fisher information, Shannon and approximate entropies) features. The frequency-domain features extracted from the spectrum of EEG signals include: power spectrum-based (e.g. spectrum normalized power and sub-band powers), spectral-based (e.g. spectral flux, centroid, Roll-Off and flatness), and entropy-based (e.g. spectral entropy) features. The time-scale features are extracted from the mutli-scale representation (e.g. wavelets and X-lets) of the EEG signal and include: the statistics of the details coefficients of the EEG signal (e.g. mean, variance, zero-crossing rate, etc.) and their relative energies. In the T-F domain, the features are extracted from the T-F representation of the EEG signal and include the non-stationary features -that are able to characterize the non-stationary nature and multi-component characteristics of the EEG signal- such as the instantaneous frequency and those based on signal and image processing techniques, recently proposed in [3, 4, 5].

As EEG signals are non-stationary with time-varying frequency contents, a time-frequency signal analysis is used to characterize the seizure activity present in these signals. This study aims to define new T-F features class by translating some relevant time-domain and frequency-domain features

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to the joint T-F domain in order to improve the performance of EEG seizure detection and classification systems. The translated features are then ranked and selected according to maximal-relevance and minimal-redundancy criteria in order to define the optimal set of relevant features thus making it possible to reduce the computation cost of these systems.

## 2. EEG SEIZURE DETECTION AND CLASSIFICATION

### 2.1. Time-frequency representations

In order to develop EEG seizure detection and classification methods in the T-F domain, it is necessary to select a suitable T-F Representation (TFR) to represent the non-stationary EEG signals. The most common are Quadratic Time-Frequency Distributions (QTFDs) such as the Wigner-Ville Distribution (WVD), Smoothed WVD (SWVD), Choi-Williams Distribution (CWD), Modified-B Distribution (MBD) and Spectrogram (SPEC) [2].

For a given analytic non-stationary signal $z[n]$ associated with the real discrete time signal $x[n], n = 0, 1, \ldots, N-1$, the discrete version of a QTFD is given by

$$\rho[n,k] = 2 \underset{n \to k}{\mathrm{DFT}} \left\{ G[n,m] \underset{n}{*} (z[n+m]z^*[n-m]) \right\} \quad (1)$$

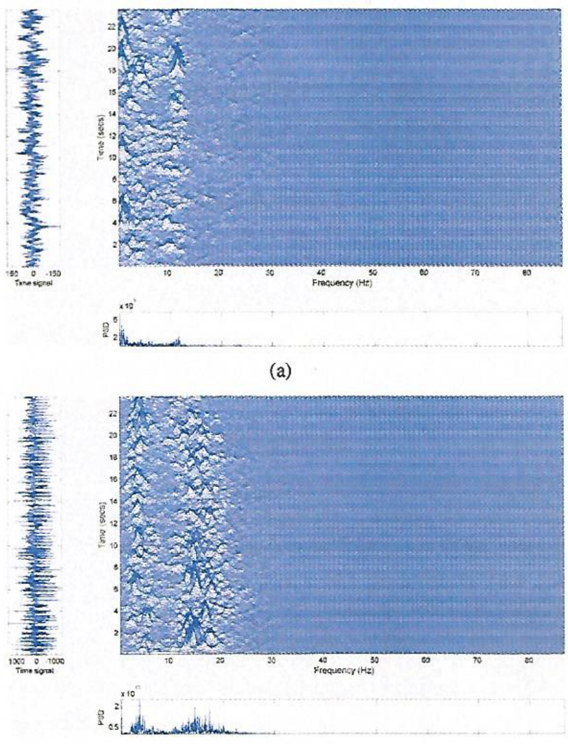
where $G$ is the time-lag kernel of the TFD and $\underset{n}{*}$ stands for convolution in time. $\rho[n,k]$ is represented by an $N \times M$ matrix $\rho$ where $M$ is the number of FFT points used ($N \geqslant M$) in calculating the TFD. Note that $n = t.f_s$ and $k = \frac{2M}{f_s} f$ where $t$ and $f$ are, respectively, the continuous time and frequency variables, and $f_s$ is the sampling frequency of the signal.

### 2.2. T-F analysis for EEG seizure detection

The TFR shows the start and stop times of signal components and their frequency range, as well as the component variation in frequency with time. Figure 1 shows an example of EEG signal with seizure and non-seizure activities in the time, frequency and joint T-F domains, in order to illustrate the difference between them and show how the QTFD plot can provide more information about the non-stationary nature and multi-component characteristics of the EEG signals than the time or the frequency representations [3, 4, 5].

### 2.3. T-F approach for EEG classification

Based on the EEG classification system described in [3, 4, 5], the T-F approach for automatic classification of EEG seizure activity proposed in this study includes the following steps: (1) finding the optimal TFR that better represent EEG signals, (2) selecting and extracting features which characterize the seizure pattern from this TFR, and (3) finally allocating the vector containing these features to the relevant class using a multi-class classifier. The selected and extracted T-F features need have the ability to discriminate between different classes in the classification system.



(b)

**Fig. 1.** An example of EEG signal with (a) non-seizure and (b) seizure activities, in the time, frequency and joint T-F domains. The TFR have been generated using SWVD.

## 3. T-F FEATURE SELECTION AND EXTRACTION METHODOLOGY

### 3.1. T-F features translation

Here, we propose a new T-F features class defined by translating and/or calibrating some most relevant time-domain and frequency-domain features to capture the signals of seizure activities in non-stationary EEG signals with a view to classify them in the joint T-F domain. Tables 1 and 2 show the relevant time-domain and frequency-domain features that have been selected in this study and their translated/calibrated version in the T-F domain. The relevant time-domain features selected include: average amplitude, derivatives of the signal's amplitude and entropy-based features [6, 7, 8, 9]. For the frequency domain, the relevant features selected include: power spectrum-based and entropy-based features [6, 7, 8].

We note that the mappings of frequency-domain features involve a summation along the time axis of TFRs so as to translate them by transforming them with a frequency domain representation (assuming that the marginals are satis-

**Table 1.** Time-domain features and their T-F translated version. *(Given a real discrete time EEG signal $x$, then $z$ and $\rho$ are the analytical signal obtained using the Hilbert transform and the QTFD of $z$, respectively.* $\mathbf{F}^{(\mathbf{t})}$ *and* $\mathbf{F}^{(\mathbf{tf})}$ *stand respectively for the features in the time domain and the translated features in the T-F domain).*

| **Time features ($\mathbf{F}^{(\mathbf{t})}$)** | **T-F translated features ($\mathbf{F}^{(\mathbf{tf})}$)** |
|---|---|
| Statistical moments-based features: | |
| • Mean, variance, skewness and kurtosis of the EEG signal [6, 7] | |
| $F_1^{(t)} = \mu = \frac{1}{N}\sum_{n=1}^{N} \lvert z[n]\rvert$ | $F_1^{(tf)} = \mu_{(t,f)} = \frac{1}{NM}\sum_{k=1}^{M}\sum_{n=1}^{N} \rho[n,k]$ |
| $F_2^{(t)} = \sigma^2 = \frac{1}{N}\sum_{n=1}^{N} (\mu - \lvert z[n]\rvert)^2$ | $F_2^{(tf)} = \sigma_{(t,f)}^2 = \frac{1}{MN}\sum_{k=1}^{M}\sum_{n=1}^{N} (\mu_{(t,f)} - \rho[n,k])^2$ |
| $F_3^{(t)} = \frac{1}{N\sigma^3}\sum_{n=1}^{N} (\lvert z[n]\rvert - \mu)^3$ | $F_3^{(tf)} = \frac{1}{(NM-1)\sigma_{(t,f)}^3}\sum_{k=1}^{M}\sum_{n=1}^{N} (\rho[n,k] - \mu_{(t,f)})^3$ |
| $F_4^{(t)} = \frac{1}{N\sigma^4}\sum_{n=1}^{N} (\lvert z[n]\rvert - \mu)^4$ | $F_4^{(tf)} = \frac{1}{(NM-1)\sigma_{(t,f)}^4}\sum_{k=1}^{M}\sum_{n=1}^{N} (\rho[n,k] - \mu_{(t,f)})^4$ |
| • Coefficient of variation of the EEG signal [6] | |
| $F_5^{(t)} = \frac{\sigma}{\mu} = \frac{\sqrt{F_2^{(t)}}}{F_1^{(t)}}$ . | $F_5^{(tf)} = \frac{\sigma_{(t,f)}}{\mu_{(t,f)}}$ |
| Amplitude-based features: | |
| • Median absolute deviation of the EEG amplitude [7] | |
| $F_6^{(t)} = \frac{1}{N}\sum_{n=1}^{N} (\lvert z[n] - \mu\rvert)$ | $F_6^{(tf)} = \frac{1}{NM}\sum_{k=1}^{M}\sum_{n=1}^{N} \lvert\rho[n,k] - \mu_{(t,f)}\rvert$ |
| • Root mean square (RMS) amplitude [8] | |
| $F_7^{(t)} = \sqrt{\frac{\sum_{n=1}^{N} z[n]^2}{N}}$ | $F_7^{(tf)} = \sqrt{\frac{\sum_{n=1}^{N}\sum_{k=1}^{M} \rho[n,k]}{NM}}$ |
| • Inter-quartile range (IQR) [9] | |
| $F_8^{(t)} = z[\frac{3(N+1)}{4}] - z[\frac{N+1}{4}]$ | $F_8^{(tf)} = \frac{1}{M}\sum_{k=1}^{M} \left(\rho[\frac{3(N+1)}{4}, k] - \rho[\frac{N+1}{4}, k]\right)$ |
| Entropy-based feature: Shannon entropy [7, 8] | |
| $F_9^{(t)} = -\sum_{n=1}^{N} z[n]\log_2(z[n])$ | $F_9^{(tf)} = -\sum_{n=1}^{N}\sum_{k=1}^{M} \rho[n,k]\log_2(\rho[n,k])$ |

fied). The same applies to the time-domain features.

### 3.2. T-F translated features selection

The translated features listed in Tables 1 and 2 can be ranked and selected in order to determine the most relevant features with minimum redundancy and maximum relevance. This can be done using the mutual information defined in [11], allowing us to select the relevant features according to *Maximum relevance* and *Minimum redundancy* criteria. We use in this study the feature selection method called mRMR (minimum-Redundancy-Maximum-Relevance), proposed by [11]. This method allows to select the maximum relevant features with a minimum redundancy using mutual information measure.

## 4. EXPERIMENTAL RESULTS AND DISCUSSION

The performance of the translated T-F features for EEG seizure classification is assessed using the real adult EEG database described in [12]. It consists of 5 sets of data referred as sets A-E. Each set contains 100 free-artefact single-channel EEG segments with duration of 23.6 seconds acquired from normal subjects and patients with epileptic seizures. Each EEG segment in each set has been recorded at $f_s = 173.6$Hz sampling rate and and therefore has $23.6 \times f_s = 4096$ samples. The desired classification is in two different classes of EEG signals, namely: **N** and **S**. The class **N** includes set A which contains 100 EEG segments without seizure acquired from 5 healthy volunteers with eye open and the class **S** includes set E which contains 100 EEG segments with seizure acquired from 5 patients. Each class has 100 EEG segments.

The T-F feature set $\mathbf{F}^{(\mathbf{tf})} = \{F_1^{(tf)}, \ldots, F_{16}^{(tf)}\}$, was extracted from the TFR of each EEG segment of length 2.95 seconds (with $N = 512$ samples). For practical considerations in terms of relevance, only the five QTFDs are chosen in this simulation: WVD, SWVD, CWD, MBD and SPEC. The parameters of the MBD and CWD were respectively chosen as $\beta = 0.01$ and $\sigma = 0.9$ with lag window length of 127. The window $w[n]$ for the SWVD and SPEC distributions was chosen to be a Hanning window of length $\lfloor N/4 \rfloor$ samples. For performance evaluation, a multi-class SVM classifier was trained using the features extracted from EEG signals in the database. We compared the classification results for each QTFDs. The database $\{\mathbf{N}, \mathbf{S}\}$ that includes 200 EEG segments was split randomly in two parts; 30% of the data (i.e., 60 segments with 30 segments in each class) were used for training and 70% (i.e., 140 segments with 70 segments in each class) for testing the classifier.

Table 3 shows the total classification accuracy results using both original time-domain and frequency-domain features $\{\mathbf{F}^{(\mathbf{t})}, \mathbf{F}^{(\mathbf{f})}\}$ and their T-F translated features $\mathbf{F}^{(\mathbf{tf})}$ extracted from different QTFDs of EEG segments. One can notice that the translated features improve significantly the classification results compared to the use of original features $\{\mathbf{F}^{(\mathbf{t})}, \mathbf{F}^{(\mathbf{f})}\}$ by up to 2% for 140 EEG segments. This is confirmed by the *total classification accuracy* calculated for each QTFD where the best result is obtained using the SWVD and SPEC; and is 98.57% for 140 EEG segments. These results confirm that including T-F features improves the EEG seizure classification performance. This can be improved by increasing the number of EEG segments in the training-step.

To assess the relevance of the proposed T-F features in the

**Table 2.** Frequency features and their T-F translated version. *(For a real discrete time EEG signal $x$, then $Z$ and $\rho$ are the Fourier transform of the analytic signal $z$ and the QTFD of $z$, respectively. Also, $\mathbf{F}^{(\mathbf{f})}$ and $\mathbf{F}^{(\mathbf{tf})}$ stand respectively for the features in the frequency domain and the translated features in the T-F domain).*

| Frequency features ($\mathbf{F}^{(\mathbf{f})}$) | T-F Translated features ($\mathbf{F}^{(\mathbf{tf})}$) |
|---|---|
| Power spectrum-based feature: maximum power of the frequency bands [6, 8]<br>$F_1^{(f)} = \sum_{k=1}^{\delta} \lvert Z[k]\rvert^2$<br>$F_2^{(f)} = \sum_{k=\delta+1}^{M} \lvert Z[k]\rvert^2$<br>In this study, only two sub-bands were considered using the EEG data described in Section 4 | $\left.\begin{array}{l} F_{10}^{(tf)} = \sum_{n=1}^{N} \sum_{k=1}^{M_\delta} \rho[n,k] \\ F_{11}^{(tf)} = \sum_{n=1}^{N} \sum_{k=M_\delta+1}^{M} \rho[n,k] \end{array}\right\} \simeq$ Sub-bands energies<br>where $M_\delta = \lfloor M/f_s \rfloor$ |
| Spectral-based features:<br>• Spectral flux: difference between normalized spectra magnitudes [7]<br>$F_3^{(f)} = \sum_{k=1}^{M} \left(Z^{(l)}[k] - Z^{(l-1)}[k]\right)^2$<br>$Z^{(l)}$ and $Z^{(l-1)}$ are normalized magnitude of the Fourier transform at $l$ and $l-1$ frames | $F_{12}^{(tf)} = \sum_{n=1}^{L} \sum_{k=1}^{P} (\rho[n,k] - \rho[n+L,k])^2$<br>$L$ is a predetermined lag and $P$ is the total of sub-bands |
| • Spectral centroid: average signal frequency weighted by magnitude of spectral centroid [7]<br>$F_4^{(f)} = \frac{\sum_{k=1}^{M} k\lvert Z[k]\rvert}{\sum_{k=1}^{M} \lvert Z[k]\rvert}$ | $F_{13}^{(tf)} = \frac{\sum_{k=1}^{M} k\rho[n,k]}{\sum_{k=1}^{M} \rho[n,k]}$ ($\simeq$ instantaneous frequency) |
| • Spectral Roll-Off (i.e. spectral concentration below threshold) [7]<br>$F_5^{(f)} = \lambda \sum_{k=1}^{M} \lvert Z[k]\rvert$<br>In this study, $\lambda$ is chosen to be 0.85 ($\simeq$ frequency under which 85% of the signal power resides) | $F_{14}^{(tf)} = \lambda \sum_{n=1}^{N} \sum_{k=1}^{M} \rho[n,k]$ |
| • Spectral flatness: indicates whether the distribution is smooth or spiky [7]<br>$F_6^{(f)} = \left(\prod_{k=1}^{M} Z[k]\right)^{\frac{1}{M}} \left(\sum_{k=1}^{M} Z[k]\right)^{-1}$ | $F_{15}^{(tf)} = \frac{\left(\prod_{n=1}^{N} \prod_{k=1}^{M} \rho[n,k]\right)^{\frac{1}{NM}}}{\sum_{k=1}^{M} \sum_{n=1}^{N} \rho[n,k]}$ ($\simeq$ Energy localization) |
| Spectral entropy-based feature: measure the regularity of the power spectrum of the EEG signal [8]<br>$F_7^{(f)} = \frac{1}{\log(M)} \sum_{k=1}^{M} P(Z[k]) \log P(Z[k])$ | $F_{16}^{(tf)} = \frac{1}{1-\alpha} \log_2 \left(\sum_{n=1}^{N} \sum_{k=1}^{M} \rho^{\alpha}[n,k]\right)$ ($\simeq$ Rényi entropy) |

EEG classification system, the translated features are ranked by order of maximum-relevance and minimum-redundancy criteria, for each QTFD. Table 4 shows the rank of the translated features obtained using mRMR method [11]. Note that the rank is based on the entropy score according to the minimum redundancy-maximum-relevance criteria [11]. One can notice by observing the top-ranked features that the following features: $\left\{F_2^{(tf)}, F_8^{(tf)}, F_{11}^{(tf)}, F_{14}^{(tf)}\right\}$ are the most relevant features for the most QTFDs. This is confirmed by assessing the performance of these selected relevant features for EEG classification. The total classification accuracy using only these 4 top-ranked T-F features is 89.29%; and exceeds the use of their original version by up to 7% (82.14%) for 140 EEG segments. Finally, the use of the relevant translated features reduces significantly the computation cost of the classification system.

## 5. CONCLUSION

This paper shows that translating the relevant time-domain and frequency-domain features into the joint T-F domain allows to define new T-F features class with better performance in EEG seizure classification. The experimental results show that the use of the selected relevant T-F features improves significantly the classification results compared to the use of their original version by up to 7%. Also, the use of the optimal relevant translated features reduces the computation cost of the classification system. Finally, the proposed T-F features can be applied to detect EEG seizures with their degree of severity (i.e., mild, moderate or severe) and their extraction can be improved using other QTFDs.

**Table 3.** Total classification accuracy results for EEG database $\{\mathbf{N}, \mathbf{S}\}$ using the T-F translated and selected features, and their original version with multi-class SVM classifier.

| Features | Total classification accuracy ( % ) |
|---|---|
| $\{\mathbf{F}^{(\mathbf{t})}, \mathbf{F}^{(\mathbf{f})}\}$ | 96.43 |
| $\{F_2^{(t)}, F_8^{(t)}, F_2^{(f)}, F_5^{(f)}\}$ | 82.14 |

| Features | Total classification accuracy ( % ) | | | | |
|---|---|---|---|---|---|
| | WVD | SWVD | CWD | MBD | SPEC |
| $\mathbf{F}^{(\mathbf{tf})} = \{\mathbf{F}^{(\mathbf{t})}, \mathbf{F}^{(\mathbf{f})}\}$ | 97.14 | 98.57 | 97.14 | 97.14 | 98.57 |
| $\{F_2^{(tf)}, F_8^{(tf)}, F_{11}^{(tf)}, F_{14}^{(tf)}\}$ | 88.57 | 88.57 | 88.57 | 89.29 | 89.29 |

**Table 4.** Ranking of the T-F translated features based on the combination of the minimum-redundancy and maximum-relevance criteria.

| Rank | WVD Feature | SWVD Feature | CWD Feature | MBD Feature | SPEC Feature |
|---|---|---|---|---|---|
| 1 | $F_2^{(tf)}$ | $F_2^{(tf)}$ | $F_2^{(tf)}$ | $F_2^{(tf)}$ | $F_2^{(tf)}$ |
| 2 | $F_8^{(tf)}$ | $F_{16}^{(tf)}$ | $F_8^{(tf)}$ | $F_8^{(tf)}$ | $F_8^{(tf)}$ |
| 3 | $F_{11}^{(tf)}$ | $F_{11}^{(tf)}$ | $F_{11}^{(tf)}$ | $F_{11}^{(tf)}$ | $F_{11}^{(tf)}$ |
| 4 | $F_{14}^{(tf)}$ | $F_{14}^{(tf)}$ | $F_{14}^{(tf)}$ | $F_{13}^{(tf)}$ | $F_{14}^{(tf)}$ |
| 5 | $F_{12}^{(tf)}$ | $F_{12}^{(tf)}$ | $F_{12}^{(tf)}$ | $F_{14}^{(tf)}$ | $F_{12}^{(tf)}$ |
| 6 | $F_9^{(tf)}$ | $F_9^{(tf)}$ | $F_9^{(tf)}$ | $F_{12}^{(tf)}$ | $F_9^{(tf)}$ |
| 7 | $F_1^{(tf)}$ | $F_4^{(tf)}$ | $F_1^{(tf)}$ | $F_9^{(tf)}$ | $F_5^{(tf)}$ |
| 8 | $F_{15}^{(tf)}$ | $F_1^{(tf)}$ | $F_5^{(tf)}$ | $F_1^{(tf)}$ | $F_1^{(tf)}$ |
| 9 | $F_{16}^{(tf)}$ | $F_6^{(tf)}$ | $F_{16}^{(tf)}$ | $F_{16}^{(tf)}$ | $F_{16}^{(tf)}$ |
| 10 | $F_7^{(tf)}$ | $F_7^{(tf)}$ | $F_7^{(tf)}$ | $F_7^{(tf)}$ | $F_7^{(tf)}$ |
| 11 | $F_6^{(tf)}$ | $F_8^{(tf)}$ | $F_6^{(tf)}$ | $F_6^{(tf)}$ | $F_6^{(tf)}$ |
| 12 | $F_3^{(tf)}$ | $F_{15}^{(tf)}$ | $F_{13}^{(tf)}$ | $F_{15}^{(tf)}$ | $F_{15}^{(tf)}$ |
| 13 | $F_{13}^{(tf)}$ | $F_{13}^{(tf)}$ | $F_3^{(tf)}$ | $F_5^{(tf)}$ | $F_3^{(tf)}$ |
| 14 | $F_5^{(tf)}$ | $F_5^{(tf)}$ | $F_{15}^{(tf)}$ | $F_{10}^{(tf)}$ | $F_{10}^{(tf)}$ |
| 15 | $F_{10}^{(tf)}$ | $F_{10}^{(tf)}$ | $F_{10}^{(tf)}$ | $F_3^{(tf)}$ | $F_4^{(tf)}$ |
| 16 | $F_4^{(tf)}$ | $F_3^{(tf)}$ | $F_4^{(tf)}$ | $F_4^{(tf)}$ | $F_{13}^{(tf)}$ |

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