Sparse Representation-based Classification of Geomagnetically Induced Currents

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Abstract—Geomagnetically Induced Currents (GIC) are the significant effects of the Geomagnetic Disturbances (GMDs) on power systems. GICs typically appear in the form of DC components in the current waveforms of high voltage transmission lines and may lead to transformer saturation, so-called DC saturation. Such saturation scenarios, if experienced, can result in severe damages to the transformer core and significantly increase the system-wide risk of major blackouts. It calls for developing detection and classification mechanisms for GICs in power systems so they can be prevented or interrupted before emerging as a threat. A major challenge associated with GIC detection is the presence of similar events, resulted from faults and other distortions, such as AC saturation caused by harmonics. The current signals recorded by current transformers can be analyzed to classify these events. In this paper, the time-frequency S-Transform is integrated with a sparsely-enhanced version of the collaborative representation-based classification to implement a fast, reliable, and adaptive GIC events classification approach. Unlike usual techniques, the proposed mechanism does not need any training procedure while, due to its linear formulation, acts inherently fast and is adaptable to recognize the challenging scenarios of combined events.

Index Terms— Smart grids, geomagnetically induced currents, transformer saturation, pattern recognition, sparse classification.

I. INTRODUCTION

Geomagnetically induced currents (GICs) have long been the cause of various power system failures, thus threatening the power system stability and security [1]. Although mitigation was traditionally the focus of research in GIC studies, the recent developments in sensing technologies bring about new opportunities to the table. Using real-time measurements from electrical currents, one can develop advanced analytical tools to detect and classify GICs from similar power quality events towards a successful and resilient GIC mitigation strategy. However, research and development efforts have not yet been focused on addressing such challenges.

A. Overview and Literature Review

Nowadays, the combination of advanced signal processing and state of the art in artificial intelligence forms the main body of the most popular frameworks in event detection and classification in a variety of monitoring and control problems including those for power system [2]. Power system events classification can be interpreted in terms of a general pattern recognition (PR) problem, that is usually split into a standard 5-step procedure as follows [3]; (1) Measurement and preprocessing, (2) Potential event pattern detection from raw data, (3) Feature Extraction (FE) from the pattern, that is widely approached by exploiting the Time-Frequency analysis including but not limited to Short Time Fourier Transform (STFT), Wavelets, S-transform, Time-Time Transform, Mathematical Morphology, etc. (please refer to [2]-[4] and references therein), (4) Feature Selection (FS) that is a set of techniques for dimensionality reduction within the feature space, thereby reducing the computational cost, and finally (5) Classification were each detected pattern is assigned to a certain class of events based on the available domain knowledge. Various methods are developed to study and implement each of these steps, including simple linear to highly complex and nonlinear algorithms, where the best approach should be selected by studying the data characteristics [5], [15].

Recently, signal analytics have been utilized in GIC-related studies. Authors of [6] developed a set of analytics to monitor GICs through processing the distorted electrical signals. These approaches, however, are not resilience to grid harmonics and their conflicts with those of GICs. Studies in [8] revealed that as the GICs intensity changes, the harmonic current magnitudes of different orders change accordingly. The application of wavelet transforms (WT) for transformer overload detection has been investigated in [7].

Most recently, and inspired by the principle concepts of pattern recognition, the authors in [22] proposed a GIC detection mechanism in transmission networks. Well-recognized time-frequency analytics, i.e., the WT and STFT, were applied for FE while a deep learning neural network (DNN) was implemented for the sake of classification. On the one hand, a major challenge with the DNN classifier training remains to be the choice of the optimal number of training data samples while decreasing the computational complexity of the training process. On the other, due to the fixed window width limitations, STFT is not capable of accurately capturing the dynamics for non-stationary signals. WT, however, perform acceptably to extract the signal information in both time and frequency domains, while is known to be more sensitive to noise.

B. Challenges, Motivations, and Contributions

For the sake of GIC detection and classification, two major sets of unresolved challenges exist among the implementation of the state-of-the-art PR-based algorithms: (1) Analytical modes, which are mostly associated with general algorithmic issues such as (1.1) optimal feature extraction, (1.2) Feature Selection is used to reduce the dimensionality of feature space and further improve the computational efficiency, (1.3) Optimal classifier training. (2) Practical modes including (2.1) Computational resource
limitations in GIC observational points such as PMU measurements in primary and secondary sides of transformers or power inverters, (2.2) no consideration to the integrated information revealed from the 3-phase systems, (2.3) Scalability and vulnerability to noise and uncertainty sources.

In this paper, we address the FE shortages through an enhanced version of a time-frequency transform named S Transform proposed in [9]. The S transform is the variable-window version of the STFT or an extension of WT, principled based on a scalable localizing Gaussian window, supplies the frequency-dependent resolution, and entirely captures the local phase information. Moreover, the theory of sparse-based classification [19] is harnessed to formulate the GIC event Classification problem as a Sparse Recovery problem with lower time and implementation complexities (GIC-SRC).

The proposed SRC framework, has variety of advantages compared to the ordinary classifiers. It is training-free approach while it offers feature independency along with the fact of bliss of dimensionality discussed in Section IV. Consequently, we do not need to put much efforts on conventional FE-FS and the parameter adjustments included in ordinary classifiers training steps. Different from the conventional classifiers, the collaborative formulation of the GIC-SRC results in higher sparsity in the proposed framework when the number of event classes increases, thereby revealing a better performance and noise robustness. These advantages, along with the linearity of the proposed GIC-SRC, considerably decrease our computational complexity and time cost while preserving a higher accuracy compared to the state-of-the-art classifiers. The performance of this method is verified over a comprehensive set of 12 GIC-polluted signal classes. We will show the superiority of the proposed GIC-SRC algorithm in comparison with other trending algorithms such as ANN [16], and SVM, and its adaptability and scalability for unexpected or drastic changes in the data characteristics.

II. PROBLEM DESCRIPTION AND TERMINOLOGY

Here we consider a balanced 110V-60Hz power system as our case study. A set of measurements including \( N = \sum_{i=1}^{M} n_i \) labeled 3p sinusoidal electrical current signals are recorded from \( J \) classes of events and are available as the training dataset. Each of these known-class vectors \( y, \in \mathbb{R}^M, i = 1, 2, \ldots, N \) represents a possible disturbance event, presumably GIC-related events. The goal is to propose an algorithm that takes a feature vector \( f_{\text{test}} \) extracted from a sample of such events \( y_{\text{test}} \), and assign it to one of the GIC-caused disturbance classes labeled as \( C_{f_j} = \{1, 2, \ldots, J\} \), in which \( D \) stands for the feature extraction operator, while the classification is represented by the operator \( A \) (which is found through the classifier training and is a nonlinear map in general). The optimal framework for the selection of these mappings is a major topic in pattern recognition literature.

The proposed GIC-SRC first implements an enhanced time-frequency decomposition technique that harnesses the flexibilities of the S-transform in time-frequency plane tiling [12] for feature extraction (hence, the first operator \( D \) is implemented). A modified sparse representation-based classification methodology is next applied for the operator \( A \). It features a reduced size of the feature vectors in the mapping \( D \). An optimal training set selection approach is pursued to identify the most informative feature vectors for each class of the disturbance event. We here split our proposed approach into two main sections: (i) Instantaneous 3-phase feature extraction via HS-Transform, (ii) Feature selection and classification using the informative sparse classifier. The entire procedure is termed here as Time-frequency-based Informative Sparse Classification for Geomagnetically Induced Currents (TISC-GIC), as demonstrated in Fig.1.

![fig1](https://example.com/fig1.png)

**Fig.1. Time-frequency decomposition based Informative Sparse Classification for Geomagnetically Induced Currents (TISC-GIC)**

III. INSTANTANEOUS 3-PHASE FEATURE EXTRACTION

In this work, a simultaneous 3-Phase Time-Frequency feature extraction is presented primarily for GIC classification. Our approach consists of 3 major steps: (1) define an alternative complex representation of 3-phase signals using power theories, (2) use Hyperbolic S-transform to integrate the benefits of the STFT and multiscale resolution of Wavelets, (3) generate an enhanced HS-Scalogram distribution as feature-images.

A. Instantaneous 3-Phase Signal Processing Tools: Direct-quadrature transformation (dq)

One may alternatively interpret a time-domain instantaneous power theory in terms of a 3D mathematical signal decomposition that maps a 3-phase waveform into a coupled, (if applicable) orthogonal feature space at each sample of time [10]. Every decomposed component in the newly formed feature space is referred to as an instantaneous power element [24]. We here employ a technique widely known as the Synchronous reference frame ($dq$). It is a combination of Park, and Concordia transforms, which converts 3-phase electrical signals into a 2 dimensional but orthogonal space. Monitoring the trajectories of the Time-Frequency Representation (TFR) of 3-phase signals under this alternative mathematical representation can form a unique, fast, and real-time GIC identifier. The dq or Park-Clark transform from abc frame to the synchronous reference frame is defined as follows [10]:

\[
\begin{bmatrix}
    d \\
    q
\end{bmatrix} = \frac{1}{\sqrt{3}} \begin{bmatrix}
    \cos(\theta) & \cos\left(\theta - \frac{2\pi}{3}\right) & \cos\left(\theta + \frac{2\pi}{3}\right) \\
    -\sin(\theta) & -\sin\left(\theta - \frac{2\pi}{3}\right) & -\sin\left(\theta + \frac{2\pi}{3}\right)
\end{bmatrix} \begin{bmatrix}
    a \\
    b \\
    c
\end{bmatrix}
\]

(1)
Where $\theta$ is the time-variant synchronization angle that represents the angular position of the $dq$ frames. Consider the orthogonality between $d$ and $q$ components one may define a combined complex signal as follows:

$$x = i_d + j i_q$$  \hspace{1cm} (2)

Although the general format of $dq$ transforms has an extra power component, namely zero component that carries the unbalanced portion of the signal, for a balanced system $x$ carries the whole 3-phase information in this new 2-dimensional mathematical domain. We may now use the TFR of this complex signal $x$ (for any GIC event captured on a 3-phase current) to form a distinctive feature space for GIC classification.

### B. Feature Extraction Through Hyperbolic S-Transform

During the last couple of decades, the Time-Frequency Representation has been a cutting-edge research area in studying the behavior of dynamic signals such as faults in electric power grids. Different from the Fourier transform, it offers simultaneous time-frequency information on the specifications of the signals’ energy and power components [11].

The S-Transform (ST) is an alternative linear TFR developed first time by Stockwell et al. in [9], [12]. S-Transform integrates the local frequency analysis of the STFT with multiscale features of WT. It can be, therefore, characterized as a multiscale local FT.

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#### A. Sparse Representation-based GIC Events Classification

In this Section, an overview of the informative sparse GIC events classification approach is presented based on the sparse representation-based classification technique [19]-[20]. We briefly review the sparse recovery theorem concepts utilized to interpret and solve the GIC-event (GICE) classification problem.

Consider $N$ number of 3-phase GICE patterns from $J$ GICE classes are recorded and available in 3-D vectors $y_j$. Using $dq$-transform an orthogonal complex alternative signal named $x_t$ is generated (2). Next, the HS-Scalogram (7) of the signal $x_t$ is computed and stored as a feature-image called $h_w(t)$.

The discrete version of the HST as follows:

$$HST(n,k) = \sum_{m=1}^{N} X(m,n) G(n,m) e^{-j \frac{2\pi}{N+1} mk}$$ \hspace{1cm} (7)

where $X(m,n)$ is the frequency-shifted discrete FT (DFT) of the discrete signal $x(n)$: $X(m) = \frac{1}{N} \sum_{n=1}^{N} x(k) e^{-j \frac{2\pi}{N+1} mk}$, and $G(m,n)$ is the DFT of a hyperbolic window $(h_w)$ defined below:

$$h_w(t) = \frac{2\alpha}{\sqrt{2\pi(\alpha+\beta)}} e^{-\frac{\alpha^2}{2\gamma^2}}$$ \hspace{1cm} (8)

$$G(m,n) = \frac{2\alpha}{\sqrt{2\pi(\alpha+\beta)}} e^{-\frac{\alpha^2}{2\gamma^2}}$$ \hspace{1cm} (9)

where $\varphi(t)$ and $\varphi(f)$ are the general representations of a hyperbolic function as follows:

$$\varphi(t) = \frac{2\alpha + \beta}{2\gamma^2} ((t-t-\xi) + \sqrt{(t-t-\xi)^2 + \gamma^2})$$ additional details on the selection of the parameters $\alpha, \beta, \gamma,$ and $\xi$ are available in [18]. In order to maintain the quadratic dependence of the signal to assure the best possible time-frequency resolution, we take the squared amplitude modulus of the HST, termed as HS-Scalogram (HSCA=|$HST|^2$), as a feature-image that can be used for further classification purposes.

### IV. INFORMATIVE SPARSE CLASSIFICATION

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$$F = [F_1 | F_2 | ... | F_J]$$ \hspace{1cm} (10)

where $T$ and $M$ indicate the number of pixels along the time and frequency axes, respectively. $F_j$ indicates the feature sub-tensor formed by the concatenation of all feature images of training GICE samples associated with the $j^{th}$ event class. According to the
sparse recovery theorems, if training data samples are fairly informative concerning the general behavior of the $j^{th}$ class, any arbitrary new feature image $f^{test}$ from a similar class can be approximately linearly-spanned by the corresponding training data; that is, for some real-valued vector $s_j \in \mathbb{R}^{n_j}$:

$$f^{test} = F_j s_j.$$  (11)

One may, alternatively, represent $f^{test}$ in terms of the entire training feature tensor as follows,

$$f^{test} = F s,$$  (12)

Back to our notation in Section II, $f^{test} = D y^{test}$ and $F = DY \in \mathbb{R}^{(T \times M) \times P}$ are the mappings of the test sample in addition to the constructed training tensor into the pre-designed feature space,
respectively; $s \in \mathbb{R}^N$ represents the sparse indicator vector. If (11)
holds, a solution to (12) exists as $s^* = [0, ..., 0, s_j, 0, ..., 0]^T$. By
definition $s$ is a sparse vector where most of the elements are equal
to zero except those associated with the $j$th GICE class. Figure 3
illustrates a visualization of such a procedure. If $F$ is formed from
an overcomplete system of linear equations, i.e., $L < N$, where
$L = T \times M$ under certain conditions, the desirable sparse format
of $s^*$, the solution of (12) can be found using the following optimization
problem:

$$P_0:\ \hat{s}_0 = \arg\min_s ||s||_0 \ \text{subject to} \ f^{\text{test}} = Fs.$$  

where the $l_0$-norm represents the number of nonzero elements in
vectors. In GICE classification, the training tensor $F$ satisfies the
underdetermined format, as the number of GICE classes $J$ is
reasonably large and enough number of training data points from
each GICE event class $c_j \ (j = 1; J)$ exists. Since $P_0$ is NP-hard, we
can, instead, use the following relaxed $l_1$-norm problem:

$$P_{N1}: \ \hat{s}_1 = \arg\min_s ||s||_1 \ \text{subject to} \ ||f^{\text{test}} - Fs||_2 < \eta.$$  

Which is equivalent to the Basis Pursuit Denoising regularization.
Variety of optimization and greedy based sparse solvers are available for solving $P_{N1}$ and the mathematical requirements for the
exact recovery of the sparse signal $s$ has been widely discussed in the
literature [19], [3] (and references there in).

Let $F = D Y$ be the training tensor created using the data points of
$J$ number of GICE classes. Also, for a given $f^{\text{test}}$, let $\hat{s}_1$ be the
optimal solution of $P_{N1}$. The selected class is attributed to a sub-
segment in vector $\hat{s}_1$ that has the minimum reconstruction residual
value. Figure 3 is a visualization of a typical SRC procedure for a
GICE event (Algorithm 1).

Algorithm 1. Informative Data Samples Selection [3]

<table>
<thead>
<tr>
<th>input:</th>
<th>Dimensionality optimized training dictionary $A \in \mathbb{R}^{L \times N}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Initiate $A$ with any arbitrary extreme point of $A$.</td>
</tr>
<tr>
<td>2</td>
<td>Find the best element that minimizes the Hausdorff distance.</td>
</tr>
<tr>
<td>$a_j^* = \arg\min_{a_j \in A}</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>$A \leftarrow A \cup a_j^*$.</td>
</tr>
<tr>
<td>4</td>
<td>Return to step if the desired $N$ or $\epsilon$ is not achieved.</td>
</tr>
</tbody>
</table>

output: Approximated training dictionary $A \in \mathbb{R}^{L \times N}$

Algorithm 2. Sparse GICE Events Classifier (TISC)

<table>
<thead>
<tr>
<th>input:</th>
<th>training data matrix $Y \in \mathbb{R}^{M \times N}$, GIC test sample $y^{\text{test}} \in \mathbb{R}^M$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Extract the feature matrix from the training data, using a random transformation matrix $D \in \mathbb{R}^{L \times N}$: $F = D Y \in \mathbb{R}^{L \times N}$. Feature extraction procedure.</td>
</tr>
<tr>
<td>2</td>
<td>Extract features of the testing data from the test sample, using the matrix $D$ used in step 1: $f^{\text{test}} = D y^{\text{test}}$.</td>
</tr>
<tr>
<td>3</td>
<td>Calculate the approximated training dictionary $A$ using Algorithm 1.</td>
</tr>
<tr>
<td>4</td>
<td>Solve $P_0$ or $P_{N1}$ for sparse vector $x^{t}_1$.</td>
</tr>
<tr>
<td>5</td>
<td>Compute purified vectors $x^{t}_1$ for $j = 1; \ldots; J$, using indicator function $g(x_i)$: $x^{t}_1 \in \mathbb{R}^L \rightarrow \mathbb{R}^k$, such that $x^{t}_1 = g(x_i)$, is a new vector whose only nonzero entries are the entries in $x_i$ that are associated with class $c_j$.</td>
</tr>
<tr>
<td>6</td>
<td>Compute residual $r_j =</td>
</tr>
<tr>
<td>7</td>
<td>$j^* = \arg\min_j r_j$.</td>
</tr>
</tbody>
</table>

output: Classify $(y^{\text{test}}) \triangleq c_{j^*}$

B. Notable Properties of TISC-GIC Approach

1. Our approach exploits the simultaneous 3-Phase information
through defining an alternative complex signal (2) compared to the
single-phase analysis, which results in missing potential couplings
between-phase relations such as unbalance.
2. With regards to the fact of “blessing of dimensionality” [19],
we can perform a random projection from feature space $F$ to an
alternative lower-dimensional feature space while not sacrificing
the recovery performance. This is equivalent in TISC-GIC, to
generate random faces from time-frequency images of the HSCA.
3. Informative sample selection can also be approached to
further optimize the number of training samples used to form the
training matrix $F$ (12). Significantly reducing the size of this
matrix and thereby, the computational cost, Algorithm 1 achieves
this goal [21].
4. Regarding our discussions in Section VI-A, due to the unique
formulation of sparse based classification, surprisingly, the more
the number of GICE classes in TISC-GIC, the sparser the pattern
of signal $s$ and the better the overall recovery performance of (14).

V. RESULTS AND DISCUSSIONS

A. Data and Feature Vectors Generation

The overall performance GIC-SRC framework has been verified over a synthesized 3-φ database that has been generated as directed in [22]-[23]. A set of 1000 event samples per class, has been generated for DC saturation (caused by GIC), normal
operational condition, and AC saturation scenarios each one
associated with three operational conditions including harmonic
distortions caused by nonlinear loads, in addition to out-of-band
interferences (OBI), and a normal waveform [23]. Therefore, 12
types of event waveforms are generated in total. The signal to
noise ratio (SNR) of all waveforms is set within 20-50 dB, randomly, to approximate the measurement noises.

To apply the S-transform on 3-φ signals first, d-q
decomposition is applied to map the current signals from the
original 3-D $i_{abc}$ domain to $i_{dq}$ domain. The $d$, $q$ components
are merged and formed a complex representation for the current
signal: $i_{dq}(t) = i_d(t) + j i_q(t)$. Fig 4a-d are illustrating the$|i_d(t)|$, blue, and $I_0(t)$, red, components for a couple of selected
saturation-related events.
TABLE I. GENERATED TRANSFORMER SATURATION-RELATED EVENTS SPECIFICATIONS [22]

<table>
<thead>
<tr>
<th>Test Case</th>
<th>Saturation Type</th>
<th>AC</th>
<th>DC</th>
<th>NO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Saturation level</td>
<td>0.001pu-0.15pu</td>
<td>0.001pu-0.15pu</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Harmonic Distortion</td>
<td>0.5 % to 10 % THD, random choose up to 50th order</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Out-of-Band Load</td>
<td>10Hz to 120Hz, level 0.01pu-0.1pu</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonlinear Load</td>
<td>1% to 20% of total load</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig 4.a-d are illustrating the $I_d(t)$, blue, and $I_q(t)$, red, components for a) DC Saturation with Harmonics, b) DC Saturation with Out of Band effect, c) Pure harmonic and d) a nonlinear load condition

**B. Results**

In this paper, combining the unique time-frequency properties of a modified version of Stockwell Transform named Hybrid S-Transform with the theory of sparse representation-based classification, we proposed a linear Time-frequency-based formulation for GIC event classification termed as TISC-GIC classifier. The main privileges of the proposed framework compared to the state-of-the-art techniques are Training-free property, feature selection independency, which eliminates all the required effort and time for FE-FS and training steps. On top of that, the linearity of GIC-SRC significantly decreases the time complexity while can easily handle the integration of a greater number of event classes within a simple matrix concatenation step (12). We verified our approach over a comprehensive set of 12 GIC polluted signal patterns generated using the IEEE standard models and compared the classification accuracy vs ANN and SVM machine as two highly recognized artificial intelligence-based classification paradigms.

**VI. CONCLUSIONS**

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