A NOVEL FUZZY C-MEAN AND S-TRANSFORM METHOD OF DISCRIMINATION AND IDENTIFICATION OF INRUSH CURRENT IN A POWER TRANSFORMER

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Abstract: *In this paper, HS-transform has been used for differentiation between inrush and fault current. Fuzzy C mean clustering technique has been used for fault current classification using Parseval's theorem calculating that energy index for various cases. Simulation of the fault (with and without noise) was done using MATLAB and SIMULINK software taken 2 cycles of data and 800. Simulation results of HS-transform have been compared with wavelet algorithm.*

Key words: *Magnetizing inrush current, Internal fault, Parseval's theorem, HS-transform, Fuzzy C-Mean*

1. Introduction.

Power transformers are important equipment in the power system and its protection scheme is of vital significance to provide continuous power supply ensuring reliable operation. When the power transformer is switched ON, the remnant flux in the transformer draws the large current from the source this current is usually ten times that of the full load current. It persists only for a very short duration and decays very quickly, which is very high magnitude causes the relay to operate falsely. Hence, such inrush current needs to be discriminated from the internal fault to prevent mal operation.

Earlier, Harmonic restraint techniques were used which discriminates inrush current from internal fault using second harmonic component [1]. Sometimes, the second harmonic component may be generated in the case of internal faults in the power transformer and this is due to Current Transformer (CT) saturation or presence of a shunt capacitor or the distributive capacitance in a long extra high voltage transmission line to which the transformer may be connected [2]. Inrush current will have dominant second harmonic component compared to internal fault. However, with improvement in transformer design, this second harmonic component is highly reduced and it was complex to discriminate using harmonic restraint techniques [3]. For the above foregoing problem, neural network and fuzzy logic techniques have also been used to detect the internal faults. In first approach[4,5]differential current harmonics were used has input to train neural network, which require large training set, large training time and design of new neural network for other transformer system having different voltage ratios and kVA rating. In another approach, fuzzy logic technique has been proposed [6, 7]. The method requires the design new rules for every cases and it is highly dependent on transformer parameter's. To overcome the above limitations, modern signal processing techniques like wavelet transform and HS-transform are required.

Recently, wavelet based algorithm have been used for power system transients [8], electrical machine analysis etc and feature extraction [9]. In [10] have used discrete wavelet transform for differential protection. In another approach [11] have used wavelet packet algorithm to extract certain features of the differential current like maximum description length, optimal wavelet and optimal levels of resolution. In [12, 13] authors have discriminated inrush and fault currents using wavelet coefficients and wavelet energy. Results are also compared with various mother wavelets. Feature extraction of differential current is also needed to reliable distinguish inrush and fault currents. In [14] authors have extracted these features using wavelet transform and neural network. In [15], have utilized wavelet transform for feature extraction and Adaptive Neuro Fuzzy Inference System (ANFIS). From the above reported literature [10-15], the variations of detailed coefficients are used to distinguish between magnetizing inrush current and fault current. This wavelet transform specifically decomposes a signal from high to low frequencies bands through an iterative procedure. This procedure performs well for high frequency transients but not so well for low frequency components that exist in magnetizing inrush current, appropriate mother wavelets have to be chosen. These tasks are very difficult as it increases the decomposition level's and leading to computation burden. Therefore, a better suitable signal processing technique has been found to recognize the current signal patterns from a transformer. The above limitations were overcome by HS-transform, which is actually a time-frequency transform [16-17]. That combines continuous wavelet transform (CWT) and STFT, S-transform is a short time Fourier transform (STFT) in that it provides time as frequency information S-transform is an extension of CWT in that it uses a variable window whose width varies with inversely with frequency content of the signal. The output of HS-transform is S-matrix whose columns are the time at which samples are taken from the signal. Thus, each column represents the real spectrum at one point in time. The S transform has two parts namely

1. The slowly varying envelope (the Gaussian function) that localizes in time.
2. The oscillatory exponential kernel that selects the frequency being localized.

The oscillatory exponential kernel is stationary and the localizing Gaussian dilates and translates. Since the oscillatory exponential kernel is stationary, the S-transform localizes real and imaginary components of the spectrum independently. Hence, it localizes the phase spectrum as well as the amplitude spectrum. This is referred to as referenced phase information. Thus, wavelet transform splits the original signal in to number of sections by scaling the frequencies and analyze them independently taking in to account separate reference for phase for each section. In this analysis, the phase information is not clearly identified. On the other hand, HS-transform uses fixed reference phase as common original signal for all sections. Hence, In the HS-Transform phase information is not lost. Further, the S-transform provides frequency contours that clearly localize the signals at a higher noise level [18]. In [19], a pattern recognition approach based on S-transform has been developed for differential protection of power transformer. Moreover, authors have not used external fault, and in this paper, for an effective protection, HS-transform has been used for feature extraction and Fuzzy C-mean for fault classification and MATLAB/SIMULINK software is considered for extensive simulation study. In their previous paper [20], the authors have addressed on using HS-transform for power transformer differential protection. In this paper, results of power transformer are analyzed through different algorithms such as HS-transform for differential protection and to ensure the feasibility of the proposed algorithm based on wavelet transform. A novel scheme to distinguish power transformer inrush current and internal fault using HS-Transform and fault identification using Fuzzy C-mean technique are presented in this paper.

2. Transient analysis based on Hyperbolic-transform

The generalized S-transform [16]can be defined as

$$s(\tau,f,p) = \int_{-\alpha}^{\alpha} h(t).w(\tau - t,f,p)e^{(-2\pi ift)} \quad (1)$$

In equation (1) h (t) is the time series of the signal to be analyzed, w(τ-t, f, p) is the window function and $e^{(-2\pi ift)}$ is the phase factor. τ is the parameter which controls the position of the window on the t axis and f is frequency of signal p denotes a set of parameter that govern the shape of window 'w'. The hyperbolic S-transform is obtained by using hyperbolic window in the place of w in Eq. (1). The hyperbolic window can be expressed mathematically as follows

$$w_{ky} = \frac{2|f|}{\sqrt{2\pi}(g_f + g_b)} X \exp\left\{\frac{-f^2\left[\chi(\tau - t,\{gf + gb, \lambda^2 hy\})\right]^2}{2}\right\} \quad (2)$$

Where

$$X(\tau - t,\{g_f, g_b, \lambda^2 hy\}) = \left(\frac{g_b + g_f}{2 g_b g_f}\right)(\tau - t - z)$$
$$+\left(\frac{g_b - g_f}{2 g_b g_f}\right)\sqrt{(\tau - t - z)^2 + \lambda^2 hy} \quad (3)$$

Z is defined as

$$z = \sqrt{\frac{(g_b - g_f)^2 \lambda^2 hy}{4.gb.gf}} \quad (4)$$

The equation [2, 3,4] are taken from reference [16], In equation 2, 3, 4 g_f is the forward taper parameter and g_b is the backward taper parameter. These two parameters determine the shape of hyperbolic window. Since event initiation, time is more important than event termination (e.g fault initiation). We use $0 < g_f < g_b$ this makes the window asymmetric with slower taper in backward direction and sharper taper in forward direction this asymmetry is needed since, its window is symmetry then if time resolution is good then frequency resolution is poor. Hence, w used asymmetric window to get good time and frequency resolution during event initiation at the expense of resolution during event termination. In (3), X is a hyperbolic in (τ-t) and depends on gf, gb and positive curvature parameter λHy which has units of time. The translation factor Z is used to make the peak of w_{Hy} to occur at τ-t =0. In (3) and (4) the radicals denote positive square root.

Where τ is the sampling interval, which is in practical applications, where capture signals are in discrete form the discrete version of ST technique is obtained by making f equals to n/NT and τ equal to KT

$$s\left[KT,\frac{n}{KT}\right] = \sum_{m=0}^{N-1} h\left[\frac{m+n}{NT}\right].G(m,n)\exp\left(\frac{2\pi inK}{N}\right) \quad (5)$$

Where, n is the total number of samples; H [m +n /NT] is Fourier transform of analyzing signals; G (m, n) is Fourier transform of hyperbolic window; K, M are discrete time indices and n is discrete frequency index k, m, n varies 0 to N-1.The computation procedure for HS-transform is given in Fig. (1)

Step.1 Obtain the samples i(t), the differential current of Iad, Ibd, Icd from the simulink model .

Step.2 Compute the discrete Fourier transform H (m, n) of i(t) using the FFT algorithm.

Step.3 Shift H (m, n) to give H (m+ n), where n is required frequency at which H is to be calculated.

Step.4 Evaluate the Hyperbolic window function (W_{hy}).

Compute the discrete Fourier transform of W_{hy} to give G (m, n) for 800 samples.

Step.5 Obtain the product of H (m+ n) and G(m, n) and take inverse Fourier transform of the product to get S transform.

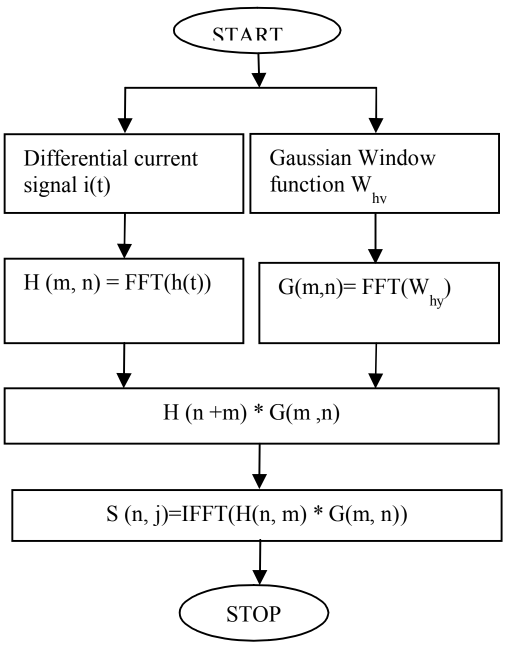


Fig.1. Flow chart for H.S Transform

3. System Investigated

The simulation model is developed using MATLAB-SIMULINK environment. The simulation model has been carried out on the system consisting of 500 MVA synchronous machine, 450 MVA with 500 kV/230 kV transformer shown in the Fig (2). The load taken here is 100 MW. The winding configuration like Y-D (Star–delta) is taken for consideration, study has been made for inrush and various internal fault conditions like winding to winding with and with out load and winding to ground. The CT's used in the primary side is delta connected and star connected in the secondary side. The relay unit is connected to CT's on both HV and LV sides.

4. Application of Parseval's theorem

The Parseval's theorem states the energy of signal i(t) remains the same whether it is calculated in the signal domain or in the transformed domain.

The Parseval's theorem is expressed mathematically as,

$$E_{\mathbf{Signal}} \frac{1}{\mathbf{T}} \int_{0}^{\mathbf{T}} |\mathbf{i(t)}|^2 \mathbf{dt} = \sum_{\mathbf{n}}^{\mathbf{N}} |\mathbf{i(t)}|^2 \qquad (7)$$

Where T and N are the time period and the length of the signal i(t). The Fourier transform of the signal is $i(t)^2$ .Using the above (7), the energy is retrieved directly from S-matrix output, and their corresponding standard deviations are obtained for inrush currents, internal faults and External faults. A fault occurs on the primary side of transformer; the respective CT's at primary side and secondary sides of the transformer captures the differential current signal. After the signal is retrieved, HS-transform is used to process the signal samples to provide the relevant features for identifying the type of fault. The energy of inrush current and fault current are computed through Parseval's theorem [21] from S-matrix output. On the other hand, the standard deviation is directly applied to the S-matrix output to derive the Standard deviation values for the corresponding phase a. The feature extraction of Energy and Standard deviation of HS-transform contour are obtained as

Energy a=(S-matrix a)^2 (8)

S-matrix a = S-matrix of phase a and

Std a=std (abs(S-matrix a)) (9)

Where, Std a = Standard deviation from S-matrix values for phase a, abs=absolute values of S-matrix.
In addition, these features have been found to be useful for discrimination of inrush current from internal fault.

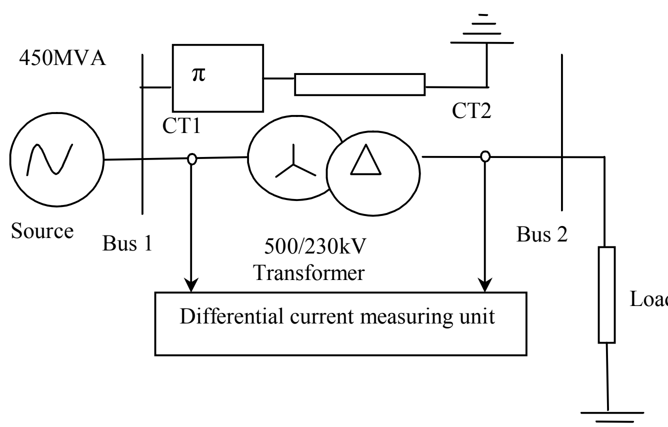


Fig.2 simulation model

5. Proposed relaying Algorithm based on HS-transform

The procedure for proposed algorithm has been given Fig.3

Step1.Obtain the samples i(t), the differential current from the simulink model

Step.2 Compute the S-transform and obtain the corresponding S-matrix

Step.3 Compute the energy matrix and standard deviation for all the values of this S-matrix.

Step.4 Average the values and get energy vector

Step.5 Set the threshold value and this threshold value is used to distinguish inrush current from fault current. If this energy vector is greater than threshold value from the fault inception; relay send should trip signal, else it should restrain.

6. Feature Extraction using HS-transform based on data Collection

Data for inrush and internal faults at various conditions like inrush, external and internal fault current for with and without load are generated using simulation model shown in Fig.2 processed through HS-transform and procedure for proposed algorithm has been given in Fig.3 generated frequency contours from S-matrix as shown in the Fig. 4 to 6. However, these frequency contours alone is not sufficient to discriminate inrush and fault current, during load and noisy conditions, it is difficult to discriminate inrush from internal fault. In addition, a Parseval's theorem has been used to extract features energy and standard deviation from frequency contours to distinguish inrush from fault current this features are shown in Tables.1 and 2. Figs.4(a-d) is magnetizing inrush current with no Load for phase a and magnetizing inrush current with no load for phase c with noise in Figs.5 (a-d) are shows that contours are interrupted in nature for inrush currents. Also, the contours are present only during the interval for which inrush current flows and the energy and standard deviation values for inrush current after HS-transform is much less compared to the internal faults. In the Figs.6 (a-d) differential current for single line to ground fault with out load for phase a and differential current for three phase fault for phase c with out load and Noise are shown in Figs.7 (a-d) it clearly shows that frequency contours are regular through out the time contours are regular through out the time series.

Table.1

Energy and Standard Deviation for inrush and internal Fault for with out load

Inrush/ Fault	**Without Load**			
	Without noise		With noise	
	Energy	Std	Energy	Std
Normal	0.0140	0.0257	0.9266	0.3
Inrush a	54.7762	2.8226	56.1941	2.75
Inrush b	11.6442	1.2993	12.6837	1.25
Inrush c	56.6961	2.8496	57.2627	2.75
Internal Faults				
Fault a-g	909.1683	8.7670	907.9308	8.76
Fault b-g	581.8270	5.7580	583.6910	5.78
Fault c-g	573.6894	6.5404	572.4685	6.52
Faultab-g(a)	1342.7	9.9700	1344.5	9.98
Faultab-g(b)	488.6363	4.7697	488.8936	4.76
Faultbc-g(b)	794.9913	6.2200	793.3062	7.18
Faultbc-g(c)	732.3477	7.9690	732.2770	7.99
Faultac-g(a)	861.8928	8.2342	864.1221	8.24
Faultac-g(c)	1325.0	10.8118	1329.1	10.9
Faultabc-g(a)	1342.7	9.9700	1346.7	10.1
Faultabc-g(b)	794.9921	6.2200	794.8671	6.3
Fault abc-g(c)	1325.0	10.8118	1324.3	10.8
External Faults				
Fault a-g	0.0012	0.0076	0.8900	0.3
Fault b-g	0.0012	0.0077	0.8277	0.3
Fault c-g	0.0012	0.0073	0.7861	0.28
Faultab-g(a)	4.6e-008	1.07e-4	0.8133	0.29
Faultab-g(b)	9.6e-004	0.0070	0.8027	0.27
Faultab-g(c)	9.5e-004	0.0070	0.8693	0.27

Table.2

Energy and Standard Deviation for inrush and internal Fault conditions for with load

Inrush/ Fault	**With Load**			
	Without noise		With noise	
	Energy	Std	Energy	Std
Normal	61.4043	1.6986	61.8211	1.8
Inrush a	54.8297	1.8471	56.8833	1.9
Inrush b	73.5018	2.2720	75.1751	2.3
Inrush c	127.475	3.039	129.4886	3.1
Internal Faults				
Fault a-g	789.276	8.0153	789.0803	8.0
Fault b-g	518.103	6.0826	521.6960	6.0
Fault c-g	405.938	5.2038	406.6147	5.3
Fault ab-g(a)	1306.4	99410	1305.8	10.1
Fault ab-(b)	612.959	6.2253	614.6860	6.3
Fault bc-g(b)	763.056	6.2402	765.7306	6.3
Fault bc-g(c)	545.951	5.9804	44.7310	6.0
Fault ac-g(a)	910.652	8.5043	12.3020	8.6
Fault ac-g(c)	984.862	8.7337	989.7062	8.8
Faultabc-g(a)	1416.0	10.3807	1417.9	10.5
Faultabc-g(b)	870.161	6.8219	72.0332	6.9
Faultabc-g(c)	1010.4	8.6122	1011.4	8.7
External Faults				
Fault a-g	18.2218	0.9256	19.2447	1.0
Fault b-g	18.2272	0.9255	18.5835	1.0
Fault c-g	18.2299	0.9255	19.4731	1.0
Fault ab-g(a)	8.2570	0.8047	9.2966	0.87
Fault ab-g(b)	9.5843	0.9107	10.5437	0.95
Fault ab-g(c)	13.8352	0.0779	14.6569	0.48

Figs.8 and 9 (a-d) shows the Magnetizing inrush current with no load for Phase a and Single line to ground fault with no load for Phase c results are obtained using discrete wavelet transform. Here wavelet transform utilizes Db9 mother wavelet function that provides series of wavelet coefficients, which translate and dilate to different frequencies unlike HS-transform and demerits are briefed in introduction. Frequency contours, generated by HS-transform are inrush and fault current that are suitable for classification by simple visual inception, but in wavelet transform, it is not possible directly. This cannot be found in wavelet transform. In this paper, Simulation results of only two cases are shown. The other cases are expected to be similar to the wavelet algorithm.

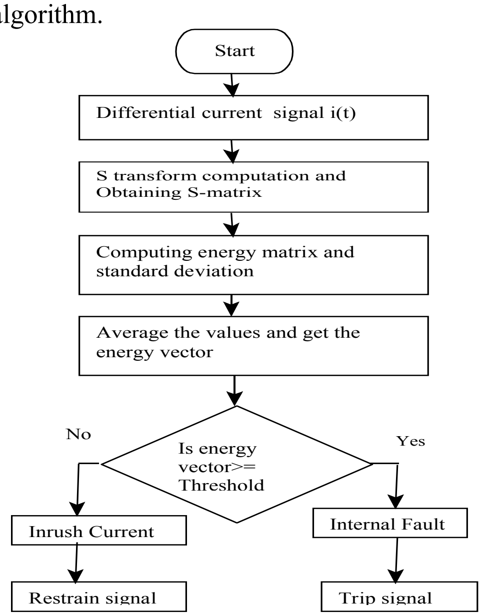
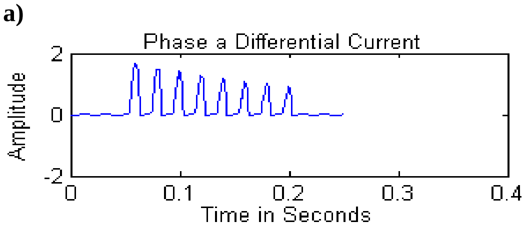


Fig.3 Flow chart for proposed algorithm using HS-Transform

Simulation Results

a)



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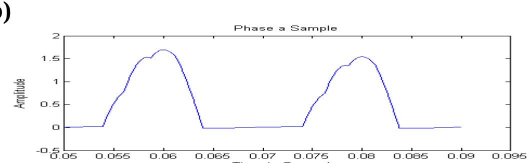

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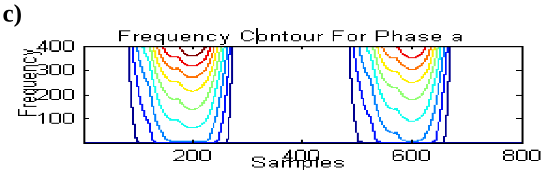

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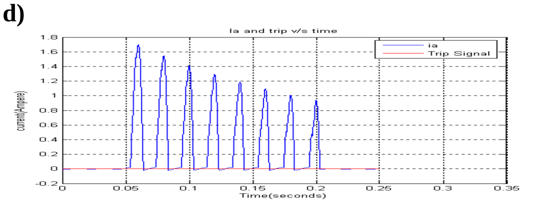
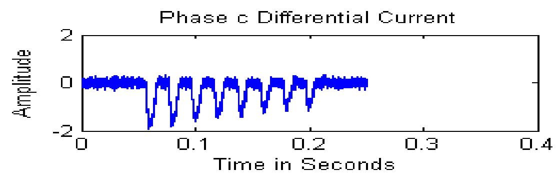


Fig.4 Magnetizing inrush current with no Load for Phase a
a) differential current, b) sampled signal
c) Frequency contours d)Trip signal

a)



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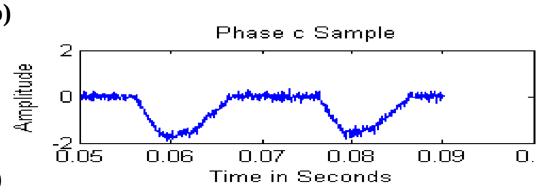

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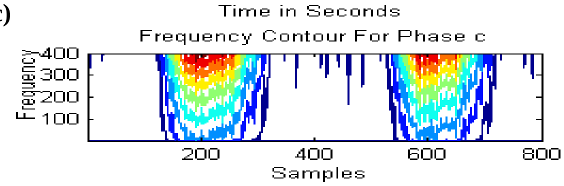

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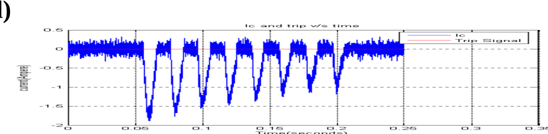
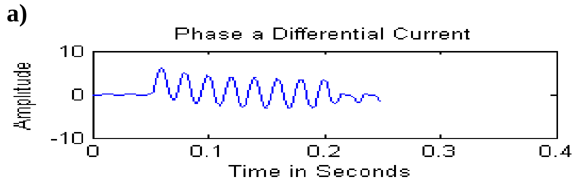


Fig.5 Magnetizing Inrush current with no load for Phase c and Noise
a) Differential current, b) Sampled signal
c) Frequency contours, d) Trip signal

a)



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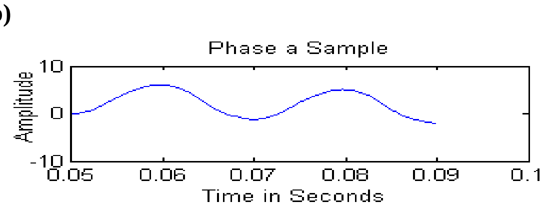

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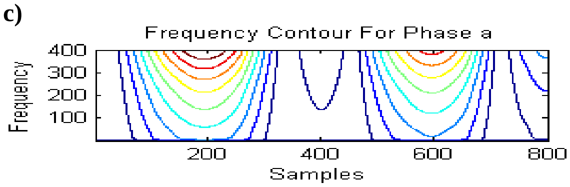

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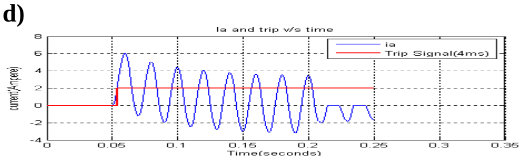
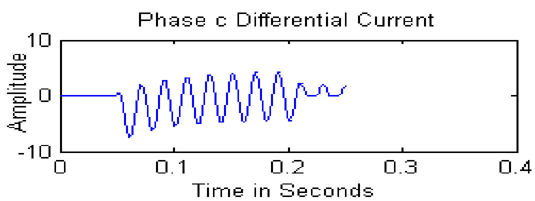


Fig.6 differential current for single line to ground fault with out load for Phase a
a) differential current, b) Sampled signal
c) Frequency contours, d) Trip signal

a)



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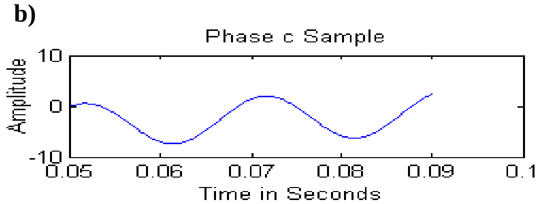

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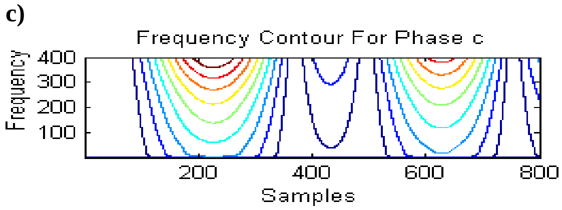

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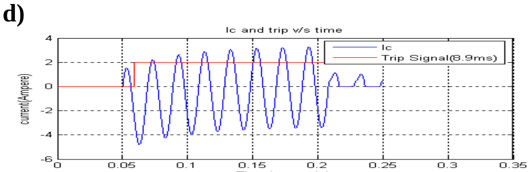
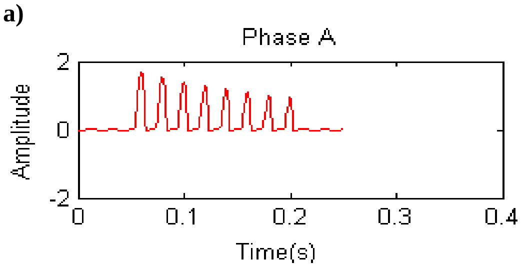


Fig.7 differential current for three phase fault for Phase c with out load and Noise
a) differential current, b) Sampled signal
c) Frequency contours d) Trip signal

a)



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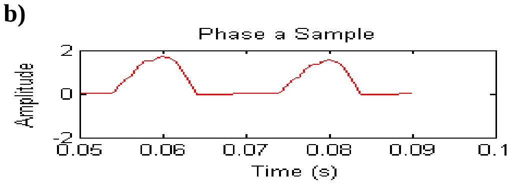

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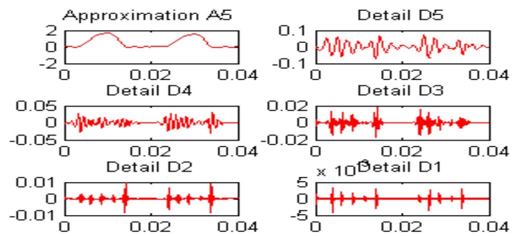
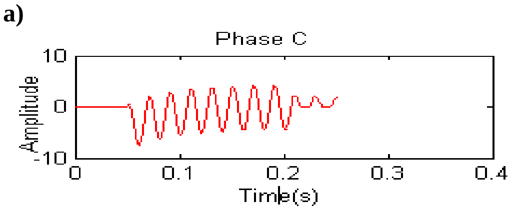


Fig.8 Magnetizing inrush current with no load for Phase a
a) differential current at Phase a, b) Sampled signal
c) Expansion of inrush current at Phase a

a)



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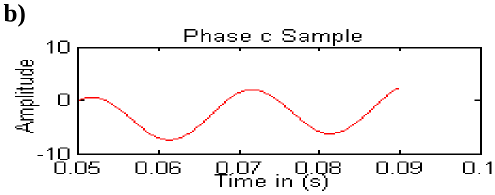

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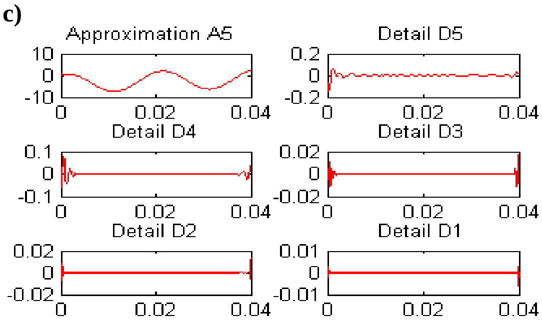

Fig.9 Single line to ground fault with no load for Phase c
a) Differential current at Phase c, b) Sampled signal
c) Expansion of internal fault at Phase c

7. Power transformer Fault classification Using Fuzzy C-Mean Clustering

Fuzzy C-Mean Clustering **(**FCM) is performed by Fuzzy logic tool box .The purpose of clustering is to identify natural grouping of data from large data set to produce a concise representation of systems behavior. The FCM starts with an initial guess for the clusters, which intended to mark the mean location of each cluster. The initial guess for these cluster centers are most likely incorrect. Next, FCM assigns every data point a membership grade for each cluster. By iteratively updating the cluster centers and the member ship grades for each data point FCM iteratively moves the cluster centers to the right location within a dataset. Data for FCM are taken from Tables.1 and 2 were energy and standard deviation are given as input to FCM.The output for FCM is shown in the Fig.10 It clearly indicates that how all the three events are discriminated from each other.(classifying the inrush current and internal fault current. Table.3 shows the number of cases simulated and results of the proposed relay. After calculating the spectral energy and standard deviation using HS Transform for inrush and internal fault current, thereby, classification of inrush and internal fault current is done by clustering technique. This clustering technique was acquired by using Fuzzy logic toolbox.

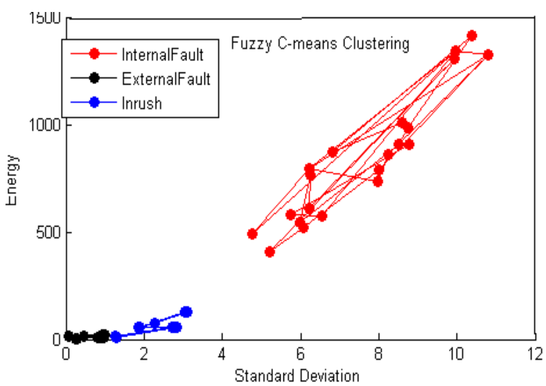

Fig.10 Fuzzy C-means clustering to discriminate inrush and internal fault

Table.3

Results of Proposed Scheme

S.No	Events	Number of Cases	.Out Put
1	Inrush Current	12	Restrain Trip Signal
2	Internal Fault	72	Send Trip Signal
3	External Fault	24	Restrain Trip Signal
4	Normal	4	Restrain Trip Signal
	Total Cases	112	

8. Conclusion

This paper presents a new technique to distinguish between the inrush and internal fault currents in power transformer using HS-Transform. A two cycles of fault current or normal current, each 400 samples are processed through HS-Transform to generate frequency contours. Using Parsevel's theorem from the frequency contours, features such as energy and standard deviations are calculated. Advantage of the proposed algorithm it works even in the presence of noise and with aid of HS-transform it can detect, localize and visually classify the transient events. Trip signal has been issued from S-matrix output. It clearly shows that trip signal is issued less than a quarter cycle. From the study of the two different algorithm, it has been found that HS-transform is clearly superior to wavelet transform even though the wavelet is more suitable for some application.

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