S.Sendilkumar
B.L.Mathur
Joseph Henry

J. Electrical Systems 6-2 (2010): x-xx

Regular paper

Differential protection of power transformer based on HS-transform and support vector machine

This paper presents a new approach to power transformer differential protection based on HS-transform and SVM (support vector machine). Here, HS-transform is used to generate frequency contours from samples of differential current and parseval's theorem is used to extract the features like energy and standard deviation. Subsequently these features are used as inputs to SVM for fault classification to identify the inrush current and fault current. The SVM is tested and trained with the features extracted from frequency contours for different fault conditions. Simulation of the fault (with and without noise) was done using MATLAB AND SIMULINK software taken 2 cycles of data each 400 samples. The advantage of the proposed algorithm provides more accurate results even with the presence of noisy inputs (Energy and standard deviation) and accurate in identifying inrush and fault currents. Overall accuracy of the proposed method is found to be 92.85%.

Keywords: HS-transform,SVM, Parseval's theorem, internal fault, Magnetizing inrush current.

1. Nomenclature

S- S-transform
τ- Controls the position of the gaussian window
f-frequency
t-time
h(t)-time series of the signal
Wgs-generalized window
P-Phase factor
gf-Forward taper parameter
gb-Backward taper parameter
λ^2 hy-hyperbolic window
ξ-translation parameter
N-Total number of samples
Std a = Standard deviation of S-matrix values for phase a
G(m,n)- denotes the Fourier transform of the hyperbolic window
H(m, n)- is the frequency shifted discrete Fourier transform
CT-Current transformer
HV- High voltage side
LV- Low voltage side
E signal – To calculate energy of the corresponding phase
abs-absolute values of S-matrix
w^T -dimensional vector
b- scalar
M- is the number of samples belong to Class –I or Class-II

Corresponding author : . S.Sendilkumar,St Peter's Engineering College,Avadi-600054
Annauniversity,Chennai,sendilkumar2009@gmail.com
B.L.Mathur,SSN college of Engineering,Kalavakkam,Anna University,Chennai
Joseph Henry,Vel tech Engineering College,Avadi,600054,Anna University,Chennai

2. Introduction

Power transformer is one of the important element in the modern power system. The protection of large transformer has become a very challenging problem for protection engineers. Thus the rapid discrimination of inrush current from internal fault is most essential to avoid the mal operations of the relay since the magnetizing inrush current, which occurs during the energization of transformer results in several times the full load current [1] Therefore such mal operation should be eliminated in order to protect the power transformers. Earlier, harmonic restrain techniques was used to discriminating inrush current and fault current based on second harmonic component [2]. Also, the second harmonic component may also generated in power transformer internal fault due to CT saturation or presence of shunt capacitance or due to distributive capacitance on long extra high voltage transmission line and found inrush current will have large second harmonic component compared to internal fault and this method was found to be inefficient[3]. Nowadays modern power transformers with improved design, this second harmonic component was greatly reduced and has difficulty to discriminate using second harmonic restraint techniques[4]. For the above foregoing problem, neural network and fuzzy logic techniques has been used to detect internal fault. In the first approach [5,6] inputs to the neural networks is the harmonic content of differential current. Neural network methods need more samples, large training set, time and design of new neural network for other transformer system which having different voltage ratios. In another approach, a fuzzy logic technique has been proposed [7,8]. The limits of these method is to design new rules for different cases and highly dependent on transformer parameter's. These require a highly improved signal processing techniques like wavelet transform WT and S-transform. In [9, 10] two different transformers having different winding configuration has been studied using WT with db2 and wavelet energy has been used to distinguish inrush and fault current. In another approach, wavelet packet algorithm based on maximum description length has been used and compared with various other mother wavelet functions [11]. On the other hand feature extraction is needed to distinguish inrush and fault current. In [12] extracted features from inrush and fault current samples are used has inputs to neural network.In [13] the authors have utilised WT for feature extraction and ANFIS (adaptive neuro fuzzy inference system) is used to distinguish inrush and fault current. In [14] wavelet based gaussian mixture has been used to identify the Magnetizing inrush current. These approaches face large training patterns and long time for training. From the above reported literature [9-14], the variations of the detailed coefficients are used to distinguish magnetizing inrush and fault current. The WT specifically decomposes a signals from high to low frequency bands through iterative procedure, and this procedure performs well for high frequency transients but not so well for low frequency transients that exits in magnetizing inrush or fault current, appropriate mother wavelet have to chosen which is very difficult and increase of decomposition levels, the computation time may increase. The above limitations are over come by using HS-transform in [15,16] has found application in geosciences and power engineering application [17,18] The S-transform is an invertible time frequency spectral localization technique that combines elements of wavelet transform and short time Fourier transform. The S-transform uses an analysis window whose width is decreasing with frequency providing a frequency dependent resolution. This transform may be seen as continuous wavelet transform with phase correction. It produces a constant relative bandwidth analysis like wavelets while it maintains a direct link with Fourier spectrum. The S-transform has an advantage in that it provides multiresolution analysis while retaining the absolute phase of each frequency. This has led to its application for power transformer fault analysis and fault identification. In [19] an pattern recognition approach using S-transform with complex window and ADALINE is used to distinguish inrush and fault current. The feature extraction from the fault current signal, a variant of the original S-transform is used where a pseudo Gaussian hyperbolic window is used to provide better time and frequency resolution at low and high frequencies unlike the S-transform using a Gaussian window. Here the hyperbolic window has frequency dependence in its shape in addition to its width and height. The increased asymmetry of the window at low frequencies leads to an increase in the width in the frequency domain, with consequent interference between major noise frequencies. In this paper, A two cycles of fault current or normal current are processed to HS-transform that produces frequency contours and using parsevals theorem features such as energy and standard deviation are calculated from S-matrix and SVM is trained and tested with the features from frequency contours. The simulation studies of transformer different faults have been carried out using MATLAB/SIMULINK and HS-transform has been implemented using MATLAB (M File) environment [20]. The SVM technique[21] has also been implemented in MATLAB environment using bioinformatics tool box. Advantage of the proposed algorithm provides more accurate in representing the signals in the pattern recognition form, More over HS-transform are able to handle the signals with polluted noise.

3. Variant of S-Transform - Hyperbolic-Transform

The expression of the original signal [15] is defined as

$$S(\tau, f) = \int_{-\alpha}^{\alpha} h(t).\left\{ \frac{|f|}{\sqrt{2\pi p}} \exp(\frac{\left[-f^2(\tau - t)\right]}{2}) \times e^{(-2\pi ft)} \right\} dt \tag{1}$$

In Equation 1 . where S-denotes the S-transform of h(t), which is actual fault current signal varying with time frequency is denoted by f, and the quantity τ is a parameter which controls the position of Gaussian window on the time-axis.

The generalized S-transform is obtained from the original S-transform by replacing the Gaussian window with a generalized window, the expression is given by

$$Wgs(\tau - t, f, p) = \frac{|f|}{\sqrt{2\pi p}} \exp(\frac{\left[-f^2(\tau - t)\right]}{2p^2}) dt \tag{2}$$

$$S(\tau, f, p) = \int_{-\alpha}^{\alpha} h(t).w(\tau - t, f, p) e^{(-2\pi ift)} \, \mathrm{dt} \tag{3}$$

In Equation 3. 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 of the t-axis and f is frequency of signal denotes a set of parameter that govern the shape of window ‘w’.

In applications, which require simultaneous identification of time-frequency signatures of power transformer were inrush and internal fault current, it may be advantageous to use a window having frequency dependent asymmetry. Thus, at high frequencies where the window is narrowed and time resolution is good, more asymmetrical window needs to be chosen. On the other hand at low frequencies the window is wider and frequency resolution is less critical, more asymmetrical window may be used to prevent the event appearing too far ahead on the S-transform. Thus an hyperbolic window of the form given below is used

$$W_{ky} = \frac{2|f|}{\sqrt{2\pi}(g_f + g_b)} \mathrm{X} \exp\left\{ \frac{-f^2\left[\chi(\tau - t, \left\{gf + gb, \lambda^2 hy\right\})\right]^2}{2} \right\} \tag{4}$$

where

$$X\left(\tau - t,\left\{g_f, g_b, \lambda^2 hy\right\}\right) = \left(\frac{g_b + g_f}{2 g_b g_f}\right)(\tau - t - \xi) + \left(\frac{g_b - g_f}{2 g_b g_f}\right)\sqrt{(\tau - t - \xi)^2 + \lambda^2 hy} \quad (5)$$

In the above expression $0<g_f< g_b$ and ξ is defined as

$$\xi = \sqrt{\frac{(g_b - g_f)^2 \lambda^2 hy}{4.gb.gf}} \quad (6)$$

The translation by ξ ensures that the peak of w_{Hy} to occur at τ-t =0
In Equation 5 and 6 the radicals denotes positive square root.

The discrete version of the hyperbolic S-transform of the internal fault current and inrush current is calculated as

$$s\left[KT, \frac{n}{KT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right].G(m,n)\exp\left(\frac{2\pi imK}{N}\right) \quad (7)$$

Where N is the total number of samples, H [m+n / NT] is Fourier transform of analyzing signals, G (m , n) denotes the Fourier transform of hyperbolic window and the indices n, m, k are n=0, 1,….,N-1,m=0,1….N-1 and k=1, 1,…..N-1

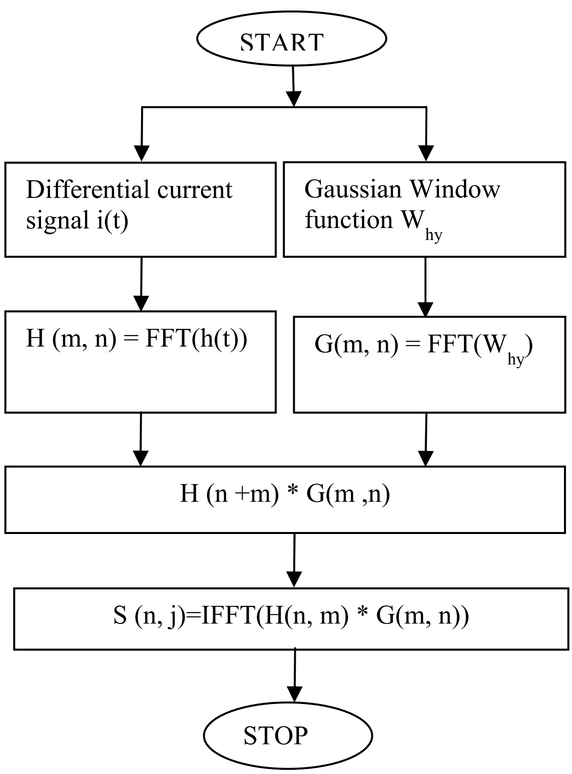


Fig. 1: Flow chart for H.S Transform

The computation procedure for HS- transform is given in Figure 1

- Obtain the samples i(t), the differential current from the simulink model .
- Compute the discrete Fourier transform H (m, n) of i (t) using the FFT algorithm.
- Shift H (m, n) to give H (m+ n), where n is required frequency at which H is to be calculated.
- Evaluate the Hyperbolic window function (W_{hy}).

- Compute the discrete Fourier transform of W_{hy} to give G (m, n) for 400 samples.
- Obtain the product of H (m+ n) and G(m, n) and take inverse Fourier transform of the product to get S-transform.

4. System Studied

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 Figure 2. The load taken here is 100 MW and 80 MVAR. 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 of the transformer. The sampling rate is chosen 20 kHZ. A cycle contains 400 samples to process inrush and fault current. The generator X/R ratio is 10. The primary winding voltage, R(pu) and L(pu) are 500 kV, 0.0078 and 0.259 and secondary winding voltage, R(pu) and L(pu) are 230 k.V, 0.0078 and 0.259 respectively. In order to investigate the proposed approach under noisy conditions, random noise with SNR up to 20db has been added to the differential current signal.

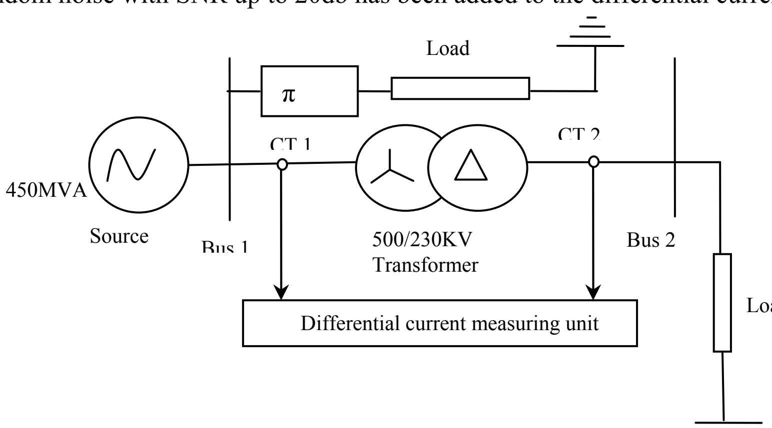


Fig. 2: Simulation model for power transformer

5. Application of Parseval's theorem

The Parseval's theorem is expressed mathematically as [22],

$$E_{Signal} \frac{1}{T}\int_{0}^{T} \left|i(t)\right|^{2} dt = \sum_{n}^{N} \left|i(t)\right|^{2} \tag{8}$$

transform of the signal is $i(t)^2$ .Using Equation 8 , the energy is computed from S-matrix and their corresponding standard deviations are calculated for inrush, internal and External faults; Later these are found to be useful in identifying inrush and fault current.

The features of Energy and Standard deviation are extracted from HS-transform contour are as follows

Energy a = (S-matrix a) ^ 2 (9)

S-matrix a = S-matrix of phase a and Std a = std (abs (S-matrix a)) (10)

In addition, these features have been found to be useful for discrimination of inrush current from internal fault.

6.Feature Extraction Using HS-transform

The Data for inrush and internal faults at various conditions like inrush, external and internal fault current for with and without load are generated from the simulation model using Figure. 2 and processed through HS-transform which generates frequency contours from S-matrix are shown in the Figure 3 to 6. But these frequency contours alone is not sufficient to discriminate inrush and fault current. During load and noisy conditions, it is difficult to discriminate inrush current from internal fault. In addition, a parseval theorem is used to extract features such as energy and standard deviation from frequency contours to distinguish inrush from fault current features are shown in Table. 1 and 2. Figure 3(a-d) Magnetizing inrush current with no load for phase a and Figure 4 (a-d) Magnetizing inrush current with no load for phase c with noise are shows that contours are interrupted in nature for inrush currents and the energy and standard deviation values for inrush current after HS-transform is much less compared to the internal faults. The Figure 5(a-d) is differential current for single line to ground fault with out load for Phase a and Figure 6 (a-d) is differential current for three phase fault for phase c with out load shows that the frequency contours are regular for three phase ground fault. Figure 7 (a-d) is Magnetizing inrush current with no load for Phase a and Figure 8 (a-c) is Single line to ground fault with no load for Phase c shows the results of DWT (discrete wavelet transform). Here wavelet transform utilized with Db9 mother wavelet function and its demerits are briefed in introduction. It is found that the localization and visualization of fault currents are better in HS-transform compared to wavelet transform. Simulation results of only two cases are shown. The other cases are to be similar to this using wavelet algorithm.

Table.1.Energy and standard deviation values for inrush and internal fault for with out load (Y-D)

Inrush/ Fault	With out Load			
	With out noise		With noise	
	Energy	Std	Energy	Std
Normal	0.0140	0.0257	0.9266	0.2926
Inrush a	54.7762	2.8226	56.1941	2.7326
Inrush b	11.6442	1.2993	12.6837	1.2483
Inrush c	56.6961	2.8496	57.2627	2.7446
Internal Faults				
Fault a-g	909.1683	8.7670	907.9308	8.7564
Fault b-g	581.8270	5.7580	583.6910	5.7728
Fault c-g	573.6894	6.5404	572.4685	6.5198
Fault ab-g(a)	1342.7	9.9700	1344.5	9.9784
Fault ab-g(b)	488.6363	4.7697	488.8936	4.7580
Fault bc-g(b)	794.9913	6.2200	793.3062	7.1766
Fault bc-g(c)	732.3477	7.9690	732.2770	7.9680
Fault ac-g(a)	861.8928	8.2342	864.1221	8.2322
Fault ac-g(c)	1325.0	10.8118	1329.1	10.8385
Fault abc-g(a)	1342.7	9.9700	1346.7	9.9958
Fault abc-g(b)	794.9921	6.2200	794.8671	6.2431
Fault abc-g(c)	1325.0	10.8118	1324.3	10.7969
External Faults				
Fault a-g	0.0012	0.0076	0.8900	0.2872
Fault b-g	0.0012	0.0077	0.8277	0.2696
Fault c-g	0.0012	0.0073	0.7861	0.2716
Fault ab-g(a)	4.6e-008	1.07e-4	0.8133	0.2679
Fault ab-g(b)	9.6e-004	0.0070	0.8027	0.2641
Fault ab-g(c)	9.5e-004	0.0070	0.8693	0.2781

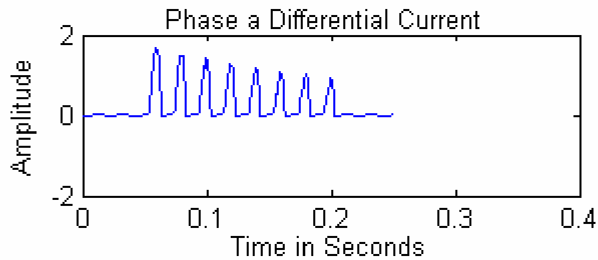
Table.2. Energy and standard deviation values for inrush and internal fault for with load (Y-D)

Inrush/ Fault	With Load			
	Without Noise		With Noise	
	Energy	**Std**	**Energy**	**Std**
Normal	61.4043	1.6986	61.8211	1.7052
Inrush a	54.8297	1.8471	56.8833	1.8722
Inrush b	73.5018	2.2720	75.1751	2.2821
Inrush c	127.4756	3.039	129.4886	3.0903
Internal Faults				
Fault a-g	789.2764	8.0153	789.0803	8.0233
Fault b-g	518.1037	6.0826	521.6960	6.0874
Fault c-g	405.9382	5.2038	406.6147	5.2083
Fault ab-g(a)	1306.4	99410	1305.8	9.9667
Fault ab-g(b)	612.9595	6.2253	614.6860	6.2282
Fault bc-g(b)	763.0560	6.2402	765.7306	6.2786
Fault bc-g(c)	545.9511	5.9804	44.7310	5.9548
Fault ac-g(a)	910.6520	8.5043	12.3020	8.5131
Fault ac-g(c)	984.8629	8.7337	989.7062	8.7349
Fault abc-g(a)	1416.0	10.3807	1417.9	10.408
Fault abc-g(b)	870.1615	6.8219	72.0332	6.8490
Fault abc-g(c)	1010.4	8.6122	1011.4	8.6068
External Faults				
Fault a-g	18.2218	0.9256	19.2447	1.0084
Fault b-g	18.2272	0.9255	18.5835	0.9958
Fault c-g	18.2299	0.9255	19.4731	0.9954
Fault ab-g(a)	8.2570	0.8047	9.2966	0.8606
Fault ab-g(b)	9.5843	0.9107	10.5437	0.9547
Fault ab-g(c)	13.8352	0.0779	14.6569	0.4737

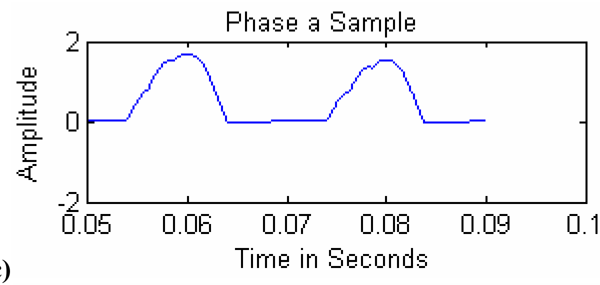
Table.3. Energy and standard deviation values for internal fault at secondary side (Y-D)

Fault at Secondary side	With Load			
	Without Noise		With Noise	
	Energy	**Std**	**Energy**	**Std**
Fault a-g	126.0581	3.1395	127.1003	3.1481
Fault b-g	159.2741	3.7655	160.0184	3.7866
Fault c-g	75.3524	1.9637	75.7037	1.9860
Fault ab-g(a)	606.8445	7.0973	605.1514	7.1048
Fault ab-g(c)	460.8895	5.9501	460.3167	5.9509
Fault bc-g(a)	364.8739	4.6217	364.7977	4.6463
Fault bc-g(b)	496.4746	6.3088	497.8557	6.3058
Fault ac-g(b)	307.9819	4.1672	309.3073	4.1847
Fault ac-g(c)	290.2986	3.9211	292.3763	3.9484
Fault abc-g(a)	818.8844	8.0267	817.3918	8.0134
Fault abc-g(b)	534.1966	5.7150	537.3827	5.7041
Fault abc-g(c)	521.1944	5.8768	521.6019	5.9117

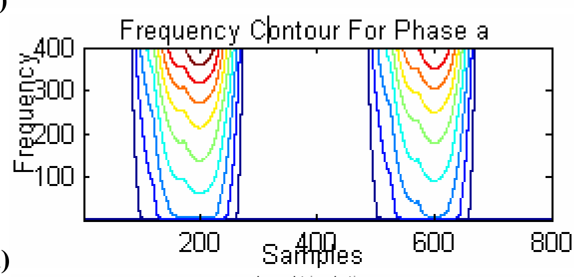
a)



b)



c)



d)

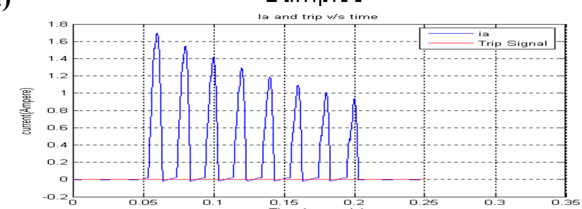
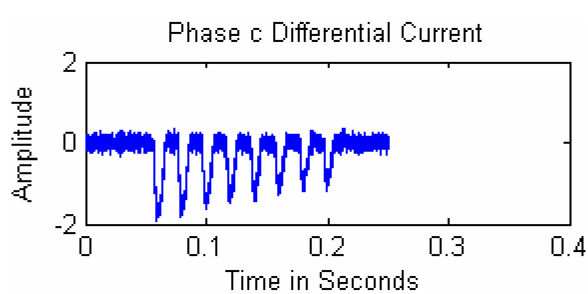


Figure. 3 Magnetizing inrush current with no Load for Phase a
a)differential current, b) sampled signal, c) Frequency contours,d)Trip signal



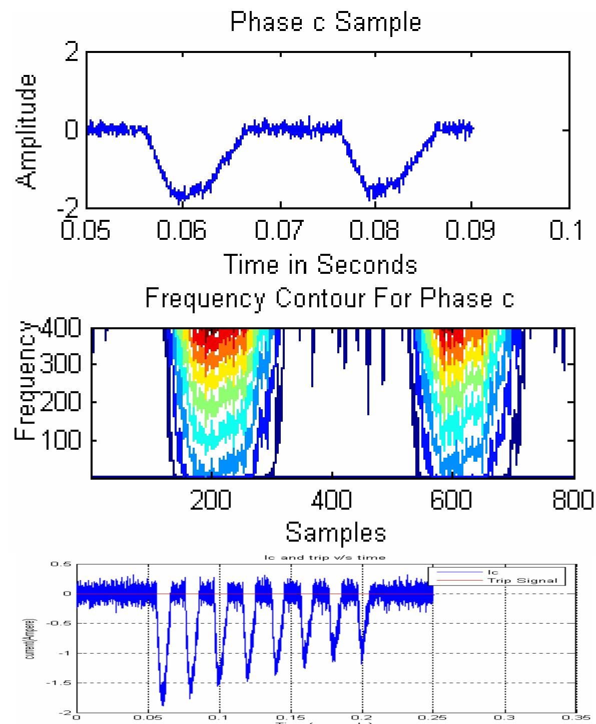
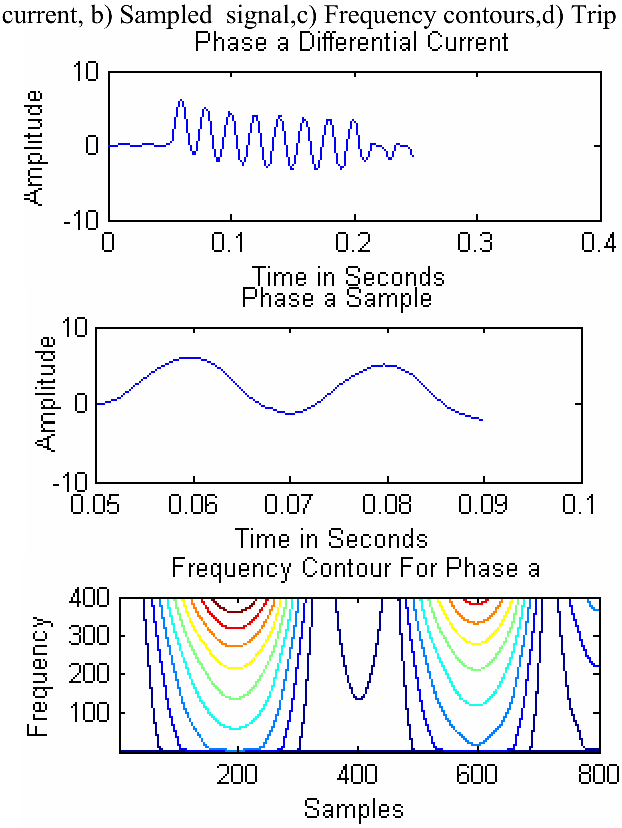


Figure.4 Magnetizing Inrush current with no load for Phase c and Noise
a) Differential current, b) Sampled signal,c) Frequency contours,d) Trip signal



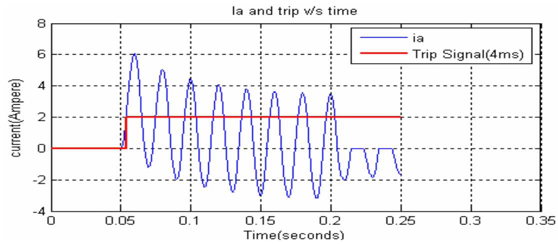


Figure.5 differential current for single line to ground fault with out load for Phase a
a) differential current,b) Sampled signal,c) Frequency contours,d) Trip signal

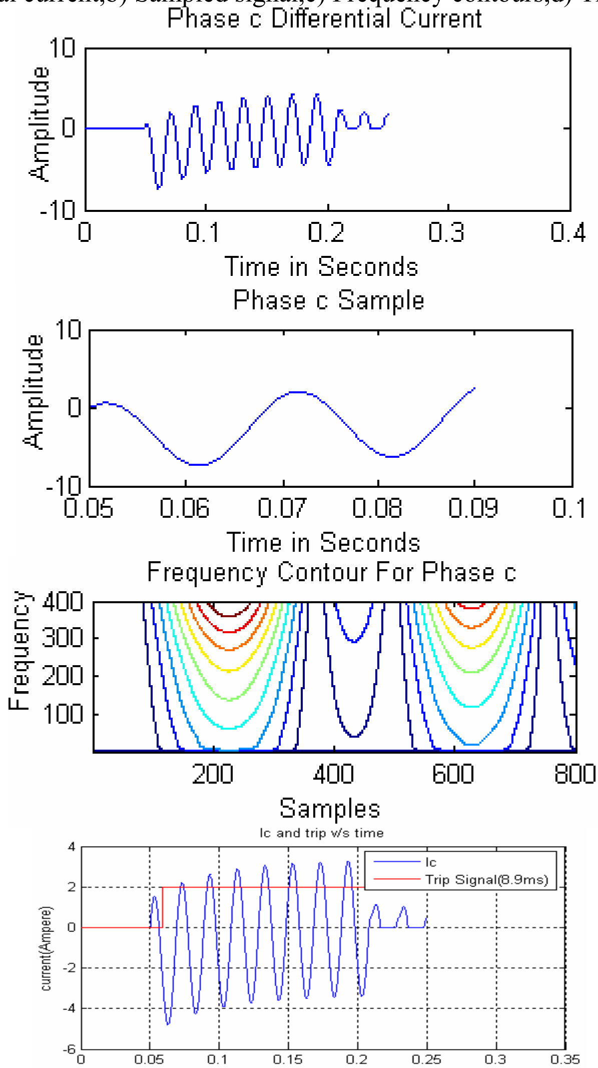
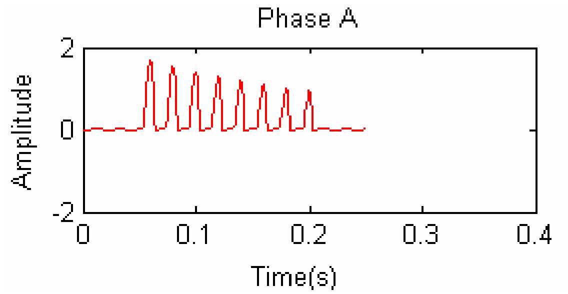
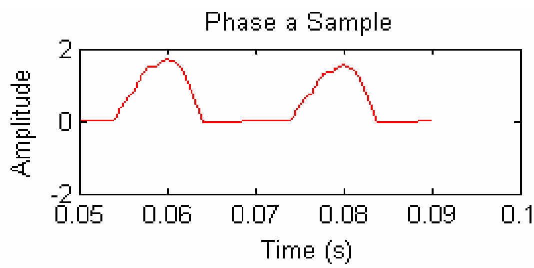


Figure.6 differential current for three phase fault for phase c with out load
a) differential current,b) sampled signal,c) Frequency contours,d)Trip signal

a)



b)



c)

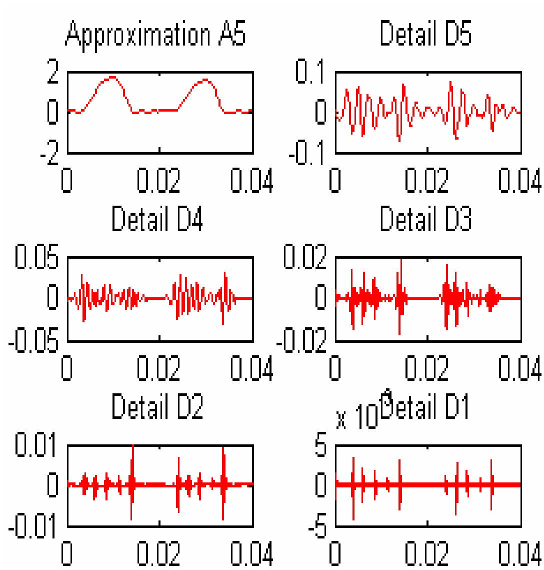
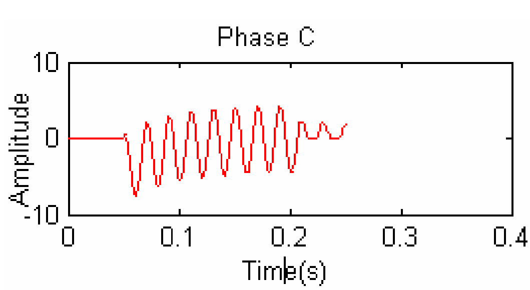
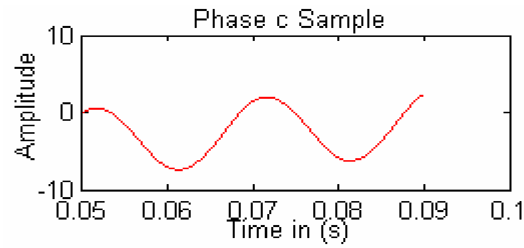


Fig. 7: Magnetizing inrush current with no load for Phase a
a)differential current at Phase a, b) Sampled signal,c) Expansion of inrush current at Phase a

a)



b)



c)

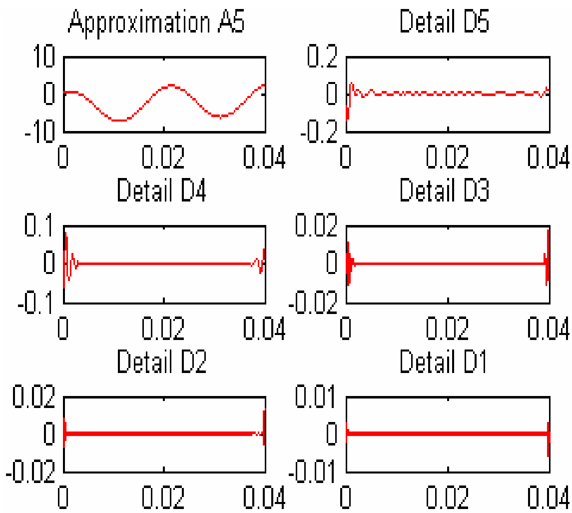


Fig.8: Single line to ground fault with no load for Phase c
a)differential current at Phase c,b)Sampled signal,c)Expansion of internal fault at Phase c

7. Support Vector Machine

SVM is a relatively new computational learning method based on the statistical learning theory. In SVM, the original input space is mapped into a high-dimensional dot product space called a feature space, and in the feature space, the optimal hyperplane is determined to maximize the generalization ability of the classifier. SVMs have the potential to handle very large feature spaces, because the training of SVM is carried out so that the dimension of classified vectors does not have as a distinct influence on the performance of SVM as it has on the performance of conventional classifiers. Also, SVM-based classifiers are claimed to have good generalization properties compared to conventional classifiers, because in training the SVM classifier, the so-called structural misclassification risk is to be minimized, whereas traditional classifiers are usually trained so that the empirical risk is minimized. SVM is compared to the radial basisfunction (RBF) neural network in an industrial fault classification task, and it has been found to give better generalization. SVMs may have problems with large data sets, but in the development of fault classification routines, these are usually not even available [23].

Let n -dimensional input Xi (i=1,2,….M), M is the number of samples belong to class-I or Class-II, and associated labels be Yi =1 for Class I and Yi = -1 for class –II, and associated labels be Yi =1 for Class I and Yi = -1 for class –II, respectively. For linearly separable data a hyperplane f (x) =0 which separates the data can determined

$$f(x) = w^T x + b = \sum_{j=1}^{n} w_j x_j + b = 0 \qquad (9)$$

Where “w ” is an dimensional vector and “ b” is a scalar. The vector “w ”and the scalar “b ” determine the position of the separating hyperplane. This separating hyperplane satisfies the constraints
F $(x_i) \geq 1$ if $y_i = 1$ and $f(x_i) \geq -1$ if $y_i = -1$ and this results in

$$y_i f(x_i) = y_i (w^T x_i + b) \geq +1 \text{ for } i = 1,2,\ldots M \qquad (10)$$

The separating hyperplane that creates the maximum distance between the plane and the nearest data is called the optimal separating hyperplane as shown in the Fig.9. The geometrical margin is found to be $\|w\|^{-2}$ [23].
Simulation of SVM classifier has been performed through MATLAB environment using Bioinformatics tool box. To evaluate the SVM, the method used in references [24] has been used for fault classification and the detailed information about the SVM can be found in Vapnik [25]

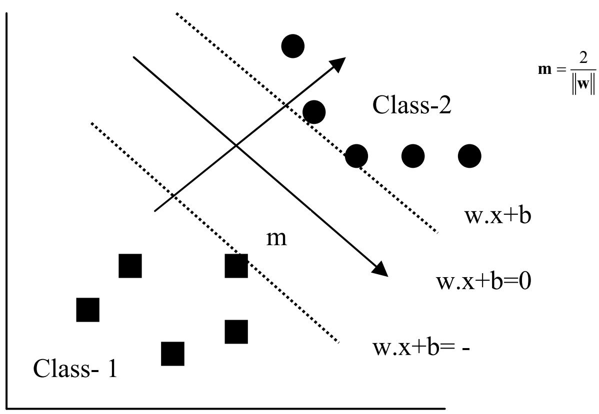


Fig. 9 : Optimal separating plane

8. Proposed Algorithm Using HS-Transform and SVM

The new method of identifying inrush current from internal fault has been presented by using HS-transform and SVM.
Figure 7 shows the procedure for fault classification, and it follows:

- obtain the samples i(t), the differential current from the simulink model.
- Compute the S-transform and obtain the corresponding S-matrix.
- For the corresponding S-matrix, compute the energy matrix and standard deviation to all values of S-matrix using parsevals theorem.
- Features from S-matrix are used for fault classification in SVM classifier based on linear kernel function.
- Extracted features are trained and tested through target values to obtain desired outputs

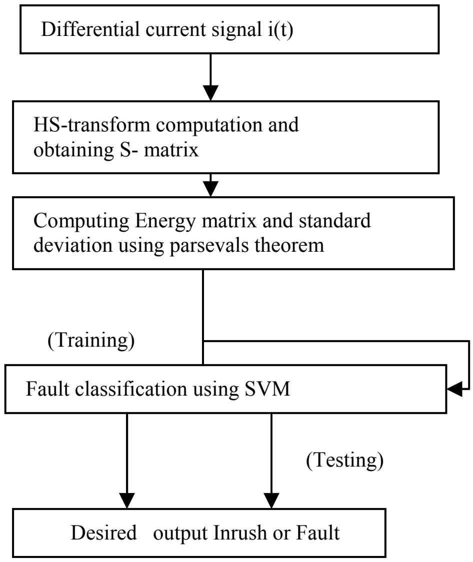


Fig. 7 : Procedure for fault classification

9. Classification of Using SVM

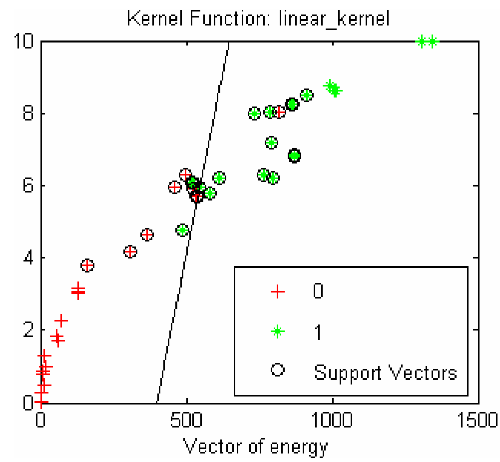
The proposed SVM classifier using linear function has been evaluated using features from Table 1 to 3. In addition, Table. 4 illustrates number of events simulated are 112 cases. In that inrush current of 12 cases, internal fault current of 72 cases and also external fault has been created on the transmission line for 24 events which are simulated and measured through respective CT's. These 112 cases are processed to HS-transform to extract features like energy and standard deviation for the above presented events and they are depicted as in the Table 1 to 3. The performances of the algorithm have also been checked by polluting the original signals with 20db noise. The extracted features from noisy signals are also shown in Table 1 to 3. These extracted features are processed to SVM have dataset of 112 x 2 (Pair of energy and standard deviation). The target has been assigned as **inrush** for No fault data i.e (Inrush, Normal and external fault) and **Internal fault** for Fault data. During training phase, Figure.8 shows that SVM classifier trained with 56 dataset ; Figure 9 shows that SVM classifier tested with 56 dataset and outputs of SVM is [+1 and 0]. The target of the SVM is built in such a way that the value "1" represents internal fault current; the value "0" represents for inrush, Normal current and external fault. Table.5 illustrates that the SVM classifier has been performed over all accuracy of 92.85%.

Table.4. Distribution of transient events

S.No	Events	No of Cases	Target	Output
1.	Normal	4	Inrush	0
2.	Inrush Current	12	Inrush	0
3.	External Fault	24	Inrush	0
4.	Internal Fault	72	Fault	1
	Total cases	112		

Table.5. Over all test results

Condition	No of patterns	Correct patterns	Incorrect patterns	Classification rate
Training	56	56	-	100
Testing	56	52	4	92.85



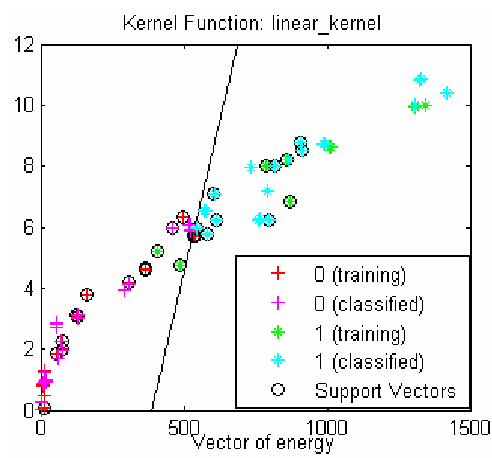


Fig.8 : Trained feature vectors for inrush and Fault current

Fig.9 : Tested Feature vectors using Inrush and Fault current

9. Conclusion

This paper presents a new technique to classify events like Inrush, fault current and external fault based on intelligent techniques. In this proposed method, frequency contours for two cycles of fault current are generated using HS-transform and features like energy, standard deviation are computed using parseval's theorem are trained and tested using SVM for fault classification. In the first stage, features like energy and standard deviation are computed for inrush, internal and external fault using HS-transform which are samples of fault current from fault inception and these features are extracted for two cycles and in the second phase identification of inrush and fault current are performed by SVM classifier using linear kernel function. The events tested by HS-transform were then compared to wavelet based differential protection algorithm which presented are inefficient to visualize the fault information. An over all accuracy has found to be 92.8524% is obtained from 112 test data. The results proved that the proposed technique based on HS-transform and SVM classifier is capable for classifying transient's events more accurately.

References

[1] M. A. Rahman and B. Jeyasurya, "A state-of-the-art review of transformer protection algorithms," *IEEE Trans. Power. Delivery*, vol. 3, pp. 534–544, April 1988.

[2] P. Liu, O. P. Malik, C. Chen, G. S. Hope, and Y. Guo, "Improved operation of differential protection of power transformers for internal faults," *IEEE Trans. Power Delivery*, vol. 7, pp. 1912-1919, Oct.1992.

[3] T.S. Sidhu, M.S. Sachdev, H. C. Wood, and M.Nagpal, "Design implementation and testing of a micro-processor-based high-speed relay for detecting transformer winding faults," *IEEE Trans. Power Delivery*, vol.7, pp. 108-117, Jan 1992.

[4] P. Bastard, M. Meunier, and H. Regal, "Neural network-based algorithm for power transformer differential relays," *IEE Proc. on Gen., Trans., Distri.*, vol. 142, pp. 386-392, 1995

[5] M. Geethanjali, S.M.R. Slochanal, R. Bhavani, "PSO trained ANN-based differential protection scheme for power transformers," *Neurocomputing,* vol.71, pp. 904-918, Jan 2007.

[6] D.V. Coury and E.C. Segatto, "An alternative approach using artificial neural networks for power transformer protection," *Europ. Trans. Electric. Power,* vol. 16, pp. 63-67, Oct 2005.

[7] A. Wiszniewski, B. Kasztenny, "A multi-criteria differential transformer relay based on fuzzy logic," *IEEE Trans. Power Delivery*, vol. 10, pp. 1786-1792, Oct 1995.

[8] M.C. Shin, C. W. Park, and J.H. Kim, "Fuzzy logic-based relaying for large power transformer protection," *IEEE Trans. Power Delivery*, vol. 18, pp. 718-713, July 2003.

[9] P.L. Mao and R.K. Aggarwal, "A wavelet transform based decision making logic method for discrimination between internal faults and inrush currents in power transformers," *Electric Power System Research*, vol. 22, pp. 389-395, June 2000.

[10] A.I. Megahed, A. Ramadan, W. El. Mahdy, "Power transformer differential relay using wavelet transform energies," Proceedings of and Energy society,(PESGM"08),2008

[11] S.A. Saleh and M. A. Rahman, "Modeling and protection of a three phase power transformer using wavelet packet transform," *IEEE Trans. Power Delivery*, vol. 20, pp. 1273-1282, April 2005.

[12] P. L. Mao and R. K. Aggarwal, "A novel approach to the classification of the transient phenomena in power transformers using combined wavelet transform and neural network," *IEEE Trans. Power Delivery*, vol. 16, pp. 654-660, July 2001.

[13] H. Monsef, S. Lotfifard, "Internal fault current identification based on wavelet transform in power transformers," *Electric Power System Research*, vol. 77, pp. 1637-1645, Oct 2007.

[14] S. Jazebi, B. Vahidi, S.H. Hosseinian and J. Faiz, "Magnetizing inrush current identification using wavelet based gaussian mixture models," *simulation modelling Practice and Theory*, vol 17, pp. 991-1010, July 2009

[15] R.G.Stockwell, L.Manisha, R.P.Lowe, "Localization of the complex spectrum: S- transform," *IEEE Trans. Signal processing*, vol. 44, pp. 998-1001, April 1996.

[16] C.R. Pinnegar, and L. Mansinha, "The S-transform with windows of arbitrary and varying window," *Geophysics*, vol. 68, pp. 381–385, Jan 2003.

[17] P. K. Dash, B. K. Panigrahi and G. Panda, "Power quality analysis using S-transform," *IEEE Trans. on Power Delivery*, vol. 18, pp. 406-411, April 2003.

[18] S. R. Samantaray, P. K.Dash and G. Panda, "Fault classification and location using HS-transform and radial basis function neural network," *Electric Power System Research* ,vol.76 ,pp. 897-905, June 2006.

[19] S. R. Samantaray, B. K. Panigrahi, P. K. Dash and G. Panda, "Power transformer protection using S-transform with complex window and pattern recognition approach," *IET Generation Transmission Distribution*, Vol. 1, pp. 278-286, March. 2007.

[20] Matlab : Bioinformatics tool box,2008.Mathworks,Ver 7.4.

[21] C.-W.Hsu, C.-C.Chang, and C-J.Lin, A Practical guide to support vector classification [online].Availiable: http://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf.

[22] A. M. Gargoom, N. Ertugrul, W. L. Soong, "Automatic classification and characterization of power quality events," *IEEE Trans.Power Delivery*, Vol. 23, pp. 2417-2425, Oct 2008

[23] P.K.Dash, S.R. Samantaray and P.Ganapati, "Fault classification and section identification of an advanced series-compensated transmission line using support vector machine," *IEEE Trans on Power Delivery*, Vol. 22, pp. 67–73, March 2007.

[24] S.Tuntisk and S.Premrudeepreechacharn, "Harmonic detection in distribution systems using wavelet transform and support vector machine," Proceedings of *IEEE Powertech* 2007.

[25] V.Vapnik, The support vector method of function estimation. In J. Suykens and J. Vandewalle (Eds.), nonlinear modeling: Advanced black-box techniques Kluwer Academic Publishers.1998.