A Condition Monitoring System Based On Dyadic Wavelet Transform Using Thermal Image

S. Senthilraj, N. R. Shanker

Abstract: ***Wavelet analysis is broadly and effectively utilized in image processing and analysis. Because of the simple and fast algorithm, the dyadic wavelet transform has generally used. A dyadic wavelet transform gives an excellent output because of the different levels of the wavelet coefficient of the image. The proposed method presents an optimal value such as mean, standard deviation and entropy for the decomposition and reconstruction of the thermal image. The original results demonstrate which technique can find the induction motor faults clearly and effectively.***

Keyword: ***Thermal image, wavelet analysis, dyadic wavelet transform.***

I. INTRODUCTION

Electrical associated faults are generally occurring fault in the induction motor which will acquire more heat on both rotor and stator windings. This results in the decrease of induction motor life time. To formulate the protection system, the operation of induction motor during electrical faults are examined by both experimental and simulation methods. To detect the motor faults fastly an IR thermography camera is introduced. The thermal camera absorbs induction motor emitting infrared radiation in a non-contact way, and also the motor temperature is obtained. The IR thermal camera can produce an image of the thermal pattern known as thermogram, in which each pixel of the image has a temperature value and a pseudo-colour allotted to an arbitrary palette colours. At induction motors, a broken rotor bars faults are detected by calculating the spectral signature of the stator currents, especially the sidebands across the suppling line frequency. The amplitude of the basic frequency (50 Hz) is extensively more than the sideband amplitude. The major issue in the motor current signature analysis is to demodulate or remove the signature frequency elements under fundamental frequency. So to solve the issue a new transform demodulation algorithm is introduced. By utilizing this algorithm, three-phase currents are changed to a magnetic-torque (M-T) coordinates. Algorithm is discovered to the signature frequency elements, is demodulated in magnetising and torque-creating currents found because of transformation. Hence, the pair demodulated M-T currents offer is utilized to remove increased signature frequency elements fault, and early induction motor fault detection are comfortable to realise. With the experimental and simulated information of the broken rotor bars, demonstrates the introduced algorithm remove elaborate fault signature frequency elements, and then understand early fault of the induction motors [1].

A new technique is introduced to detect rotor eccentricity faults in a closed-loop drive-associated induction motor. Dissimilar a line-sustained electric motor, the eccentricity fault signals will be in current and also the voltage of a drive-associated motor. Interim, since speed and subsequently the mechanical load can vary wide in factors speed approach, the amplitudes of the fault signals change as needs. Artificial neural networks are utilized to detect study the complex relationship among the operating conditions and eccentricity-associated harmonic amplitudes. Neural network can forecast threshold related to operating condition, which is utilized to forecast the motor condition. Neural network is instructed and tested with information possessed on drive-associated 4-pole, 7.5 Hp, three-phase induction motors. The exploratory solutions approve the detection technique is possible above the entire range of operating conditions of the exploratory motors [2].

A non-invasive method analysis gear tooth surface faults depends on stator current space vector examination is introduced. Torque oscillation account is delivered by gear tooth surface; harm fault in mechanical torque is tested by determined electrical machine which is fundamentally examined. This account comprises of mechanical effect created by fault adopted damped oscillation that is recognised between mechanical scheme torsional common frequency and damping factor. Across hypothetical improvements, demonstrated that periodic conduct of specific shape present fault-associated frequencies in harmonics and stator current, so entire number product of rotation frequency in stator current space vector prompt frequency. Fault signature identified with the gear tooth surface harm fault is forecasted across number of simulation. A simulation outcome is approved between tests that are showing conceivable non-invasive gear tooth surface harm fault detection with a fault affectability equivalent to invasive techniques. Committed test format, given a 250W squirrel-cage three-phase induction machine shaft-associated with a single-stage gear is utilized [3].The traditional multiple single classification (MUSIC) technique is broadly utilized at induction machine fault identification and determination. The technique will remove important frequencies, however, can't supply exact amplitude data for fault harmonics. So introduced frequency examination for stator current to calculate fault-sensitive frequencies and amplitudes for broken rotor bars (BRBs). The developed technique utilizes an amplitude estimator, fault decision module and frequency estimator. The frequency estimator is carried out by zoom system and high-resolution examination method called as the approximation of signal parameters through rotational invariance methods, which separate frequency precisely. A least squares estimator is determined in the amplitude estimator to get fault harmonics amplitudes, without outflow of frequency. Fault decision module, the fault determination records in amplitude estimator is utilised relying upon the induction motors load conditions. The fault record and relating threshold were improved by utilizing false alarm and identification probabilities. Exploratory outcomes acquired in induction motors demonstrate diagnosis algorithm equipped for identifying broken rotor bars fault with an exactness better than zoom-based MUSIC algorithm [4].

Exploratory examination of mechanical faults detection in induction motor result discussed. As is sensibly well known, by methods for the study of mixes permeance and magneto-motive force (MMF) harmonics, and conceivable to forecast frequency air gap flux density harmonics which happen because of specific inconsistencies induction motor. Successively, flux density harmonics examination permits forecast stimulated currents and voltages in stator windings. Evaluating this concept, equations may help in detection of mechanical faults produced. Equations demonstrate eccentric conditions and bearing faults. The evolution of test facility in bearing fault conditions and eccentricity faults is explained. Test facility permits fast entry to motor bearings, permitting an examination concerning capacity to distinguish bearing fault conditions utilizing stator current monitoring. Test outcomes are exhibited, showing conceivable to identify bearing condition utilizing moderately easy and low-cost component [5].

Induction motors (IMs) utilized in different domestic and industrial approach. An authentic IM health monitoring system exceptionally helpful to identify IM fault at beginning stage to block execution condition of IMs and for determined components. Enhanced bispectrum (EB) method along auxiliary frequency (AF) injection (EB-AF) is introduced to guide early detection of IM fault. AFs is infused into electric current signals, to upgrade fault feature frequency elements. The EB method changes standard 2-D bispectrum having huge characteristics into one-scale spectral depiction to make easy characteristic removal for IM defect identification. Adequacy of introduced EB-AF method is analysed by IM bearing fault detection carrying various load and speed conditions. Experimental outcomes demonstrate introduced EB-AF method discover fault features adequately for starting IM fault identification [6].

Fault indicator is known as swing angle, inter-turn faults and broken-bar is examined. This indicator fault depends on rotating magnetic-field pendulous-oscillation construct defective squirrel-cage induction motors. Utilizing “swing-angle indicator,” will be exhibited currently an inter-turn fault is recognized at the presence of machine producing defects. In the interim, broken-bar fault is identified under direct-line and PWM excitations, even at hard condition of partial-load levels. Two conditions for motor manufacturing, imperfections and partial load, which are regarded as hard conditions for fault identification, and examined through the attain experimental outcomes to a set of 2-hp and 5-hp induction motors [7].

Sensor fault diagnosis and separation unit are viewed by induction-motor drives gives adaptive percipient along rotor-resistance analysis. Normally, closed-loop induction motor drives having voltage source inverters utilize dc-link voltage, position or speed, and three phase-current sensors. In developed fault diagnosis and separation unit, determines rotor resistance and phase currents are forward to decision-making unit, then detects the faulty sensor type by deterministic rule base. At current-sensor failure condition, finds phase having incorrect sensor output. This demonstrates inconsistent of early developed model-based fault-tolerant methods, utilizing bank of percipient is unimportant, and only current percipient having rotor-resistance determination adequate for separation of sensors’ faults. The developed method efficiency is analytically demonstrated. Moreover, experimental tests and extensive simulation verify the efficiency of developed technique at various operating conditions [8].

Different uses artificial neural networks (ANN’s) delivered in literature , demonstrate method appropriate to adapt online induction motors fault detection. A new methodology is introduced to discuss the electrical faults. The developed method is based on the park's vector method. Indeed, stator Current Park’s vector patterns studied, utilizing ANN’s, then utilized to distinguish among "faulty" and "healthy" induction motors. Analysis process experimented at both decentralized and classical method. Decentralized architecture aims to encourage satisfactory distributed execution of faults to starting NN monitoring system. Conclusion of the developed method experimentally analysed on 4-kW squirrel-cage induction motor. The received outcomes give satisfactory level of exactness, demonstrating promising industrial utilisation of hybrid Park’s vector-neural networks method [9].

The problem occurs in bearing failure and analysis in induction motor was discussed. Indeed, bearing disintegration is currently the primary case rotor failures in induction motor. Fault detection and diagnosis methods are briefly discussed and compared which is the Concordia transform and Park transform approach. Experimental trail, 0.75 kW two-pole induction motor along artificial bearing harm, outlines fundamental features previously mentioned method for small and medium-size induction motors bearing failure diagnosis/detection [10].

Presents system for induction motor (IM) to detect broken rotor bars, utilizing zero grouping high-frequency signal injection. Subordinates motor currents are examined, resulting signal processing permits to analyse signals how alter its value as effect of broken rotor bar in IM. The fundamental characteristic of the system is that zero grouping high-frequency signals produced by standard space vector modulation of IM drive. Experimental and analytical results are introduced, approving broken bars detection system [11].

Industrial machinery is broad utilization of induction motors as main motion supplies for related kinematic chain. Kinematic chain and motors subject to failures one or more segments making faults detection as main problem for industries. Thermography method is utilized for diagnosis and monitoring industrial facilities, it is desirable for induction motors monitoring and related kinematic chain. Thermography method guides the faults detection and analysis the operating condition of industrial machinery. A few exploration works utilized thermography, but issue is manual change that should be done by thermal camera to acquire thermal images, that present the focus object true temperature. A new methodology is introduced that modifies automatically thermal camera, utilizing additionally external temperature sensors to align the thermal images by low-cost thermal camera to yield the objects true temperature. Experimentation functions on induction motor having related kinematic chain to examine the effectiveness of proposed methodology [12].

The failures in decreasing speed gearboxes or speed multipliers with gears have generally been analyzed by methods for vibration analysis. Latterly there has been seen the opening of analyzing by tracking the stator current of the motor driving the box or its electromagnetic torque. These vibrations, dissimilar vibration studies, have the benefit of being non-invasive. The aim is to calculate the capacity of fault detection and analysis from the spectral examination of the torque. On a genuine application, the performance of the frequencies related to the fault as per the motor load condition is examined. Decisions about the theory of detecting failures of various seriousness over a tooth of a toothed wheel are acquired [13].

II. INFERENCES FROM THE LITERATURE SURVEY

Previously, an infrared-based methodology, continuous wavelet transforms, and stationary wavelet transform is utilised to analysis the induction motor fault through thermal changes. However, it has less efficiency and also to identify the secondary fault in the motor. So, the proposed the method present the results from the dyadic wavelet transform to enhance the induction motor faults with various conditions. To detect induction motor faults , a proposed method has been utilising in this process.

III. METHODOLOGY

The proposed technique is utilized to detect induction motor fault through the wavelet transform techniques. Wavelet analysis is like broadly a Fourier expansion algorithm. The deviation in wavelet can decay work to local isolating elements at various level which is particularly in favour of decimating regressive noise. Among all techniques, wavelet series denoising is most significant in wavelet analysis. To wavelet series denoising analysis, image reconstruction quality determined by singular wavelet coefficient that makes real wavelet threshold selection hard. Hardness is expected to non-redundance of image description in area of orthogonal wavelet series transform. Image description extremely excess in the area of dyadic wavelet transform due to the sub sampling isn't functioned at each dyadic wavelet transform level of image. In similar error decision probability, image denoising established dyadic wavelet transform can enhance image reconstruction quality. Finally, the technique is performed with the threshold evaluation and the wavelet coefficients.

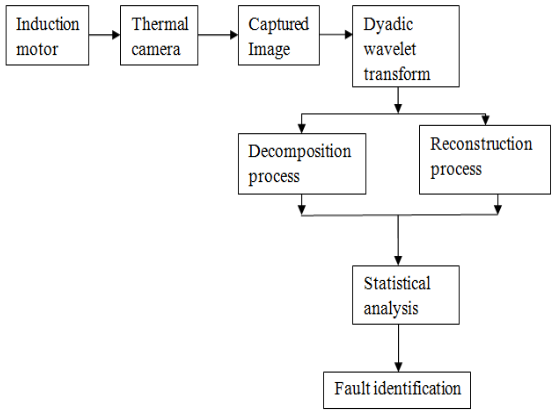


Figure 1. Block diagram for the proposed techniques.

A. Dyadic Wavelet Transform

Let the mother wavelet be $\psi(x)$; it is desired $\int_{-\infty}^{+\infty} \psi(t)\,dt = 0$, then the wavelet transforms in $L^2(R)$ is described as:

$$W_{2^j} f(x) = f^* \psi_{2^j}(x) = \int f(t)\, \psi_{2^j}(x-t)\,dt$$

Where, $\psi_{2^j}(x) = 2^{-j}\psi(2^{-j} - x)$, if its Fourier transform $\hat{\psi}(2^j\omega)$ is fulfilling the condition that A and B are constants, and A>0, B>0, $A \le \sum_{j=-\infty}^{+\infty} \left|\hat{\psi}(2^j\omega)\right|^2 \le B, \forall\omega \in R$, then to function $f(x) \epsilon L^2(R)$, at its continuous points there have

$$f(x) = \sum_{j=-\infty}^{+\infty} W_{2^j} f^* \chi_{2^j}(x) = f^* \varphi(x) + \sum_{j=-\infty}^{0} W_{2^j} f^* \chi_{2^j}(x)$$

Where $\chi(x)$ is reconstructive wavelet, $\sum_{j=-\infty}^{+\infty} \acute{\psi}(2^j\omega)\acute{\chi}(2^j\omega) = 1$, scaling function is $\varphi(x)$, $|\acute{\varphi}(\omega)|^2 = \sum_{j=-\infty}^{+\infty} \acute{\psi}(2^j\omega)\acute{\chi}(2^j\omega)$. In the above equation, the $f(x)$ value is an approximation and then explained in detail. So, the dyadic wavelet transform functions multiresolution analysis structure.

The dyadic wavelet transforms reconstruction conditions are poor than wavelet series reconstruction. For similar wavelet $\psi(x)$, its scaling function $\varphi(x)$ and corresponding reconstructive wavelet $\chi(x)$ are not sole. The discrete dyadic wavelet transforms own the similar algorithm design as discrete wavelet transform. The deviation is that filters are popularised by interpolating several 0 in discrete wavelet transform filters.

The decomposition algorithm of for dyadic wavelet transform is given below as:

$j = 0$

$while\ (j < J)$

$W^d_{2^{j+1}}f = S^d_{2^j}f * H_j$
$S^d_{2^{j+1}}f = S^d_{2^j}f * L_j$
end of while

The reconstruction algorithm for dyadic wavelet transform is given below as:

$j = J$
while $(j > 0)$
$S^d_{2^{j-1}}f = S^d_{2^j}f * \overleftrightarrow{L}_{j-1} + W^d_{2^j}f * \overleftrightarrow{H}_{j-1}$
end of while

Where $S^d_{2^j}f$ are discrete samples, $H_j = H \uparrow^{\mu}$ $L_j = L \uparrow^{\mu}$ $\bar{H}_j = \bar{H} \uparrow^{\mu}$ $\bar{L}_j = \bar{L} \uparrow^{\mu}$.

To equate with the wavelet transform, sub sampling is fail in decomposition of the dyadic wavelet transform. In the dyadic wavelet domain, the image's expression is redundant and a portion of coefficients oscillating cannot contribute to the serious distortion of the reconstructive image.

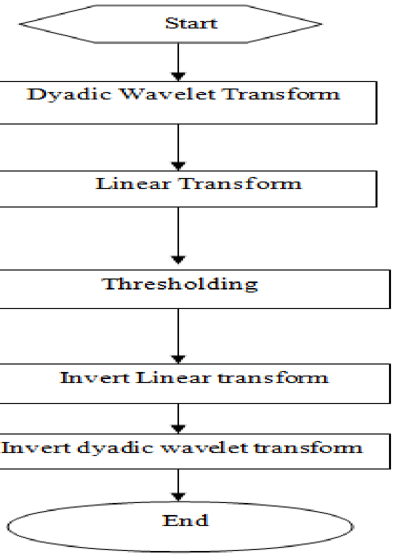


Fig 2. The flowchart of the dyadic wavelet transforms.

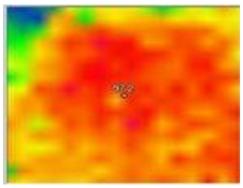
IV. RESULT AND DISCUSSION

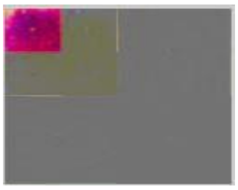
In our technique, level 5 dyadic wavelet transform image is determined and Haar families are studied. The original thermal image is divided in windows of WxH pixels. For each level, the sub-band coefficients are related to the original image window they were derived from. This spatial symmetry is needed to calculate the relevance of the data inside a image area. The performance of the wavelet coefficients must be decided in order to calculate the image quantity of data. To this function, various statistics are calculated in each sub-band of all level conceiving a window of NxM pixels. The statistical conceiving are the following: mean (1), standard deviation (2) and entropy (3).

$$Mean: \frac{\sum c(i,j)}{W.H}$$

$$Standard\ deviation: \frac{\sum (Mean - C(i,j))^2}{W.H}$$

$$Entropy: \frac{-\sum Prob(C(i,j)).\log_2(C(i,j))}{W.H}$$


(a) Original image


(b) Decomposition

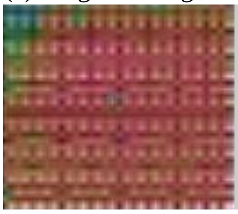
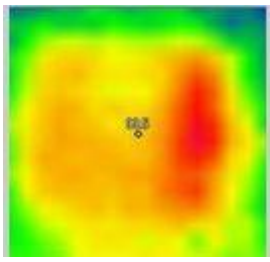

(c) Reconstruction image

Fig 3. The image of the dyadic wavelet transforms for motor off condition.


(a) Original image


(b) Decomposition

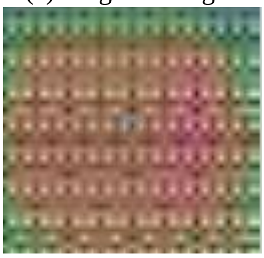
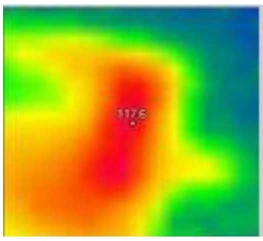

(c) Reconstruction image

Fig 4. The Image Of The Dyadic Wavelet Transforms For The No-Load Condition.


(a) Original image


(b) Decomposition

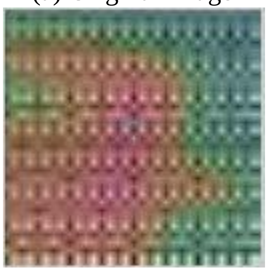
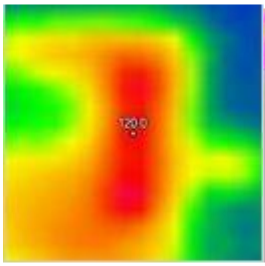
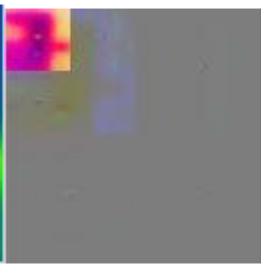

(c) Reconstruction image

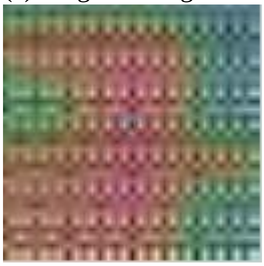
Fig 5. The Image Of The Dyadic Wavelet Transforms For An Overload Condition.



(a) Original image



(b) Decomposition



(c) Reconstruction image

Fig 6. The Image Of The Dyadic Wavelet Transforms For The Transient Condition.

In the experiments, the statistics are calculated by the windows of 5x7 pixels at each sub-bands in all wavelet level. The mean, standard deviation and entropy are calculated at different motor conditions using wavelet coefficients. The different values distinguish the induction motor conditions and given in table 1. The figure 2-5 demonstrates that the results for faulty motors related to load conditions. Figure 2 represents the motor off conditions, results of decomposition and reconstruction of dyadic wavelet transform. Figure 3 represents the no-load motor conditions, results of decomposition and reconstruction of dyadic wavelet transform. Figure 4 illustrate the motor overload conditions, outcomes of decomposition and reconstruction of dyadic wavelet transform. Figure 5 illustrate the motor transient conditions, outcome of reconstruction and decomposition of the dyadic wavelet transform. So, the developed method can effectively detect the faults by mean, standard deviation and entropy value.

Table I. The Mean, Standard Deviation, And Entropy Value For Decomposition And Reconstruction Of The Dyadic Wavelet Transform.

s.no	Motor condition	Voltage/A.c amps	Temperature (C)	Dyadic Wavelet Transform at Decomposition			Dyadic Wavelet Transform at Reconstruction		
				mean	Standard deviation	entropy	mean	Standard deviation	Entropy
1	Off	---	36.2	0.4408	0.0751	2.9245	0.3958	0.1542	7.1379
2	No load	177 v	37.5	0.4493	0.0722	2.6189	0.4423	0.1200	6.9507
3	No load	158 v	39.3	0.4236	0.0743	2.5088	0.4673	0.1254	7.0023
4	No load	135 v	40.4	0.4262	0.0774	2.7123	0.4426	0.1280	7.0474
5	No load	116 v	44.4	0.4149	0.0769	2.8681	0.4680	0.1240	7.0006
6	No load	90 v	46.0	0.4974	0.0856	2.6036	0.4495	0.1260	7.0190
7	No load	75 v	45.0	0.4374	0.0759	2.6380	0.4465	0.1273	7.0208
8	overload	0.4 amps	47.6	0.4757	0.0806	2.6479	0.4495	0.1212	6.9660
9	overload	0.8 amps	41.7	0.4988	0.0848	2.6499	0.4657	0.1199	6.9545
10	overload	1.3 amps	43.0	0.4900	0.0856	2.6499	0.4517	0.1205	6.9639
11	overload	1.7 amps	41.1	0.4790	0.0814	2.8081	0.4666	0.1203	6.9602
12	overload	2.0 amps	42.8	0.4820	0.0818	2.6784	0.4465	0.1205	6.9610
13	transient	---	48.9	0.4946	0.0843	2.6778	0.4538	0.1211	6.9650
14	transient	---	46.5	0.4508	0.0769	2.7813	0.4514	0.1233	6.9907
15	transient	---	45.5	0.4795	0.0807	2.8598	0.4246	0.1316	7.0507

V.CONCLUSION

The dyadic wavelet transform is a dominant method; the effectiveness is utilised in both the decomposition and reconstruction of the thermal image. The proposed method is functioned to find the fault at induction motors. The conclusion shows the effectiveness of the developed fault detection method under various motor load conditions like three load conditions is utilised. However, load conditions will change continuously in real applications. Future work is to determine the fault detection using various algorithms.

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