ICSIIT 2017

2017 International Conference on Soft Computing, Intelligent System and Information Technology

26-29 September 2017 • Denpasar, Bali, Indonesia

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2017 International Conference on Soft Computing, Intelligent System and Information Technology

ICSIIT 2017

Table of Contents

Preface xi

Conference Organization xii

Program Committee xiii

Reviewers xv

Classification and Correlation Techniques

Gesture Recognition for Indonesian Sign Language Systems (ISLS) Using Multimodal Sensor Leap Motion and Myo Armband Controllers Based on Naïve Bayes Classifier 1
Khamid, Adhi Dharma Wibawa, and Surya Sumpeno

Waah: Infants Cry Classification of Physiological State Based on Audio Features 7
Ramon L. Rodriguez and Susan S. Caluya

Fuzzy Clustering and Bidirectional Long Short-Term Memory for Sleep Stages Classification 11
Intan Nurma Yulita, Mohamad Ivan Fanany, and Aniati Murni Arymurthy

MFCC Feature Classification from Culex and Aedes Aegypti Mosquitoes Noise Using Support Vector Machine 17
Achmad Lukman, Agus Harjoko, and Chuan-Kay Yang

Automatic Chord Arrangement with Key Detection for Monophonic Music 21
Bor-Shen Lin and Ting-Chun Yeh

Credit Scoring Refinement Using Optimized Logistic Regression 26
Hendri Sutrisno and Siana Halim

Anomaly Detection System Based on Classifier Fusion in ICS Environment 32
Jan Vávra and Martin Hromada

Efficient Object Recognition with Multi-directional Features in Urban Scenes 39
Ryo Kawanami and Kousuke Matsushima

Feature Extraction and Image Recognition Methods

Timor Leste Tais Motif Recognition Using Wavelet and Backpropagation 45
Vasio Sarmento Soares, Albertus Joko Santoso, and Djoko Budyanto Setyohadi

The Model and Implementation of Javanese Script Image Transliteration 51
Anastasia Rita Widiarti, Agus Harjoko, Marsono, and Sri Hartati

Human Activity Recognition by Using Nearest Neighbor Algorithm from Digital Image 58
Muhammad Ihsan Zul, Istianah Muslim, and Luqman Hakim

Night to Day Algorithm for Video Camera 62
Stefan Jack Lionardi, Mariëlle Fransen, and Andreas Handojo

Arca Detection and Matching Using Scale Invariant Feature Transform (SIFT) Method of Stereo Camera 66
Aviv Yuniar Rahman, Surya Sumpeno, and Mauridhi Hery Purnomo

The Application of Deep Convolutional Denoising Autoencoder for Optical Character Recognition Preprocessing 72
Christopher Wiraatmaja, Kartika Gunadi, and Iwan Njoto Sandjaja

Acne Segmentation and Classification Using Region Growing and Self-Organizing Map 78
Gregorius Satia Budhi, Rudy Adipranata, and Ari Gunawan

Algorithms for Intelligent Computation

Extended Concept of Generalized Fuzzy Rough Sets on Asymmetric Fuzzy Coverings 84
Rolly Intan

The Proposal of the Software for the Soft Targets Assessment 90
Lucia Duricova, Martin Hromada, and Jan Mrazek

Application of Artificial Intelligence (AI) in Search Engine Optimization (SEO) 96
Yodhi Yuniarthe

Spatial Model Design of Landslide Vulnerability Early Detection with Exponential Smoothing Method Using Google API 102
Kristoko Dwi Hartomo, Sri Yulianto, and Joko Ma'ruf

Measures of Dependency in Metric Decision Systems and Databases 107
Anh Duy Tran, Somjit Arch-int, and Ngamnij Arch-int

Multiple Scattered Local Search for Course Scheduling Problem 114
Ade Jamal

The Software Proposes for Management and Decision Making at Process Transportation 120
Jan Mrazek, Lucia Duricova, and Martin Hromada

Distributed Systems and Computer Networks

A Self-Adaptive Architecture with Energy Management in Virtualized Environments 124
I Made Murwantara, Behzad Bordbar, and João Bosco Ferreira Filho

Nanoservices as Generalization Services in Service-Oriented Architecture 131
Sutrisno, Frans Panduwinata, and Pujianto Yugopuspito

Automated Concurrency Testing for Cloud-Based Polling Systems 138
Hans Dulimarta

Low-Overhead Multihop Device-to-Device Communications in Software Defined Wireless Networks 144
Riyanto Jayadi and Yuan-Cheng Lai

A Secure Anonymous Authentication Scheme for Roaming Service in Global Mobility Network 150
Kuo-Yang Wu, Yo-Hsuan Chuang, Tzong-Chen Wu, and Nai-Wei Lo

Linux PAM to LDAP Authentication Migration 155
Justinus Andjarwirawan, Henry Novianus Palit, and Julio Christian Salim

Exploratory Research on Developing Hadoop-Based Data Analytics Tools 160
Henry Novianus Palit, Lily Puspa Dewi, Andreas Handojo, Kenny Basuki, and Mikiavonty Endrawati Mirabel

Mobile and Pervasive IoT Applications

Human Heart Rate Detection Application 167
Semuil Tjiharjadi and Aufar Fajar

Near Field Communication Technology in Delivering Information in Museums 173
Djoni Haryadi Setiabudi, Ryan Christian Wiguno, and Henry Novianus Palit

Android Application for Monitoring Soil Moisture Using Raspberry Pi 178
Lily Puspa Dewi, Justinus Andjarwirawan, and Robin Putra Wardojo

Development of Mobile Indoor Positioning System Application Using Android and Bluetooth Low Energy with Trilateration Method 185
Agustinus Noertjahyana, Ignatius Alex Wijayanto, and Justinus Andjarwirawan

Assessments of Integrated IS/IT

The Proposal of United Crisis Management Information Systems of the Czech Republic 190
Katerina Vichova, Martin Hromada, and Ludek Lukas

The Analysis of Academic Information System Success: A Case Study at Instituto Profissional De Canossa (IPDC) Dili Timor-Leste 196
Apolinario Dos Santos, Albertus Joko Santoso, and Djoko Budiyanto Setyohadi

Identification of Factors Influencing the Success of Hospital Information System (SIRS) by Hot-Fit Model 2006: A Case Study of RSUD Dr Samratulangi Tondano, Minahasa Regency, North Sulawesi 202
Frendy Rocky Rumambi, Albertus Joko Santoso, and Djoko Budyanto Setyohadi

The Alignment of IT and Business Strategy at ROC Leeuwenborgh 208
Frederick Wonges, Jack Zijlmans, and Leo Willyanto Santoso

Development of Capability Assessment Model of IT Operation Management Process with Organizational Behavior 214
Luh Made Wisnu Satyaninggrat and Kridanto Surendro

Exploring Critical Success Factors of Mobile Learning as Perceived by Students of the College of Computer Studies – National University 220
Bernie S. Fabito

Identifying Characteristics and Configurations in Open Source ERP in Accounting Using ASAP: A Case Study on SME 227
Agung Terminanto and Achmad Nizar Hidayanto

Simulation and Virtual Reality Applications

The Real Time Training System with Kinect: Trainer Approach 233
Ivana Valentine Masala and Apriandy Angdresey

3D LIDAR City Model Application and Marketing Plan Development 238
Kevin Sanjaya, Frank Henning, and Kristo Radion Purba

Periodic Review Inventory Model Simulations for Imperfect Quality Items and Stochastic Demand 243
Gede A. Widyadana, Audrey T. Widjaja, and Irena Liong

Simulation on Crowd Mobility of Moving Objects Using Multi-agent and ClearPath 250
Baihaqi Siregar, Agnes Irene Silitonga, Erna Budhiarti Nababan, Ulfi Andayani, and Fahmi Fahmi

Truck Management Integrated Information System in a Shipping Line Company 257
Arnold Samuel Chan and I Nyoman Sutapa

Simulation of Atmosphere in Trowulan during the Golden Era of Majapahit
Using Virtual Reality 263
Daniel Kusuma, Rudi Adipranata, and Erandaru

Development of Interactive Learning Media for Simulating Human Digestive
System 270
Kristo Radion Purba, Liliana, and Daniel Runtulalu

Development of Interactive Learning Media for Simulating Human Blood
Circulatory System 275
Kristo Radion Purba, Liliana, and Yohanes Nicolas Paulo Kwarrie

Smart Assistive Technologies

Fall Detection Application Using Kinect 279
Kartika Gunadi, Liliana, and Jonathan Tjitrokusmo

Driver Drowsiness Detection Using Visual Information on Android Device 283
Aldila Riztiane, David Habsara Hareva, Dina Stefani, and Samuel Lukas

Epileptic Alert System on Smartphone 288
Aziis Yudha Adwitiya, David Habsara Hareva, and Irene Astuti Lazarusli

Elderly Healthcare Assistance Application Using Mobile Phone 292
Andreas Handojo, Tioe Julio Adrian Sutiono, and Anita Nathania Purbowo

Socially-Enhanced Variants of Mobile Bingo Game: Towards Personalized
Cognitive and Social Engagement among Seniors 297
Chien-Sing Lee, Shanice Wei-Ling Chan, and Sheng-Yee Guy

Smart Mobile Applications

M-Guide: Hybrid Recommender System Tourism in East-Timor 303
Jaime da Costa Lobo Soares, Suyoto, and Albertus Joko Santoso

M-Guide: Recommending Systems of Food Centre in Buleleng Regency 310
Komang Ananta Wijaya, Suyoto, and Albertus Joko Santoso

Empowering Public Secondary Schools on Disaster Response and Recovery:
A Framework for the Development of Helpline Mobile Application 315
*Odette Saavedra, Matthew C. Abrera, Mickaela Carla L. Waniwan,
Curly Kale C. Dava, and Bernie S. Fabito*

A Framework Mobile Game Application that Teaches Parts of Speech
in Grade 3 in Filipino 321
*John Erasmus Correa, Jastine Gamboa, Mark Edison Lavapie, Edzel Uy,
and Ramon L. Rodriguez*

iSagip: A Crowdsource Disaster Relief and Monitoring Application Framework 327
*Auxesis Jacobi M. Schwab, John Eduard C. Omaña, Kent V. Roazol,
Ted Anthony Y. Abe, and Bernie S. Fabito*

Case Studies of Knowledge Discovery and Management

Executive Dashboard as a Tool for Knowledge Discovery 331
Nyoman Karna

Data Mining Applications for Sales Information System Using Market Basket Analysis on Stationery Company 337
Alexander Setiawan, Gregorius Satia Budhi, Djoni Haryadi Setiabudi, and Ricky Djunaidy

A Knowledge Management-Extended Gamified Customer Relationship Management System 341
Chien-Sing Lee, Jun-Jie Foo, Vinudha a/p Jeya Sangar, Pei-Yee Chan, Weng-Keen Hor, and Eng-Keong Chan

Web Based Customer Relationship Management Application for Helping Sales Analysis on Bike Manufacturer 347
Anita Nathania Purbowo, Yulia, and Agustinus Ivan Suryadi

Replenishment Strategy Based on Historical Data and Forecast of Safety Stock 353
Allysia Ongkicyntia and Jani Rahardjo

On Estimation and Prediction of Simple Model and Spatial Hierarchical Model for Temperature Extremes 359
Indriati Njoto Bisono

Author Index 363

Timor Leste Tais Motif Recognition Using Wavelet and Backpropagation

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***Abstract*—Timor Leste is a new country of the 21st century in Southeast Asia that has a diverse culture. Tais Timor Leste has a high historical value as well as cultural identity. It is also one of the cultural heritages of Timor Leste. Tais Timor has its own characteristics and meanings in every motif, but there are still many communities of Timor Leste as well as foreign tourists who do not know the variety of the motif. Therefore, this study aimed to establish the system recognition of Tais Timor motif through the image based on the type of motif. The wavelet transform is used in the process of feature extraction and image decomposition to obtain coefficient values of which the value of energy and entropy will then be calculated. For the recognition of Tais Timor motif, backpropagation algorithm was used. This application is built using MATLAB programming language. The analysis and testing of these studies show that the accuracy of recognition of Tais Timor motif with 4 testing parameters got recognition accuracy and presentation of 80%. Thus the motif used can be identified by using both wavelet transform and backpropagation algorithm.**

Keywords—Tais Timor motif; wavelet; backpropagation; recognition; MATLAB

I. INTRODUCTION

Tais Timor Leste is a traditional form of weaving made by women of Timor Leste. It is an important part of the ancestral cultural heritage of the nation. The woven Tais Timor is used for ceremonial jewelry, home decor, and custom clothing. Tais Timo has its own designs or motifs and cultural associations. Some of the motifs and symbols that currently appear were designed before and during Portuguese times [1]. Today there are many people who are not familiar with Tais Timor motif. This Tais Timor motif which is diverse and which has a philosophical meaning and high historical value motivated the author to apply the artificial neural network technology in the form of image recognition to identify any motif that exists. The purpose of this study was that the expected method of neural networks and wavelets can be implemented to recognize each Tais Timor motif. Here are a few studies that have been conducted with the fabric research object that is "Pattern Classification of Yarn Interlacement of Fabrics Using Least Square Support Vector Machines" by Ghosh et al. [2] whose research discussed about how to read the fabric image in an attempt to interpret the pattern of interlacement thread. The subsequent research is "A New Method for the Classification of Woven Structures for Yarn Dyeing" by Zheng et al. [3] who in his research discussed the identification of structures in detecting the location of the yarn, and the yarn structure crossings in woven fabric. The other research is "Blind Wave Detection for Woven Fabrics" by Schneider and Merhof [4] whose research discussed how to ensure the quality assurance of fabrics textile. The next research is "Automatic Classification of Woven Fabric Structures Based on Texture of Features and Probabilistic Neural Network" performed by Jing et al. [5] in their research discussing how to perform a classification based on the characteristics of woven fabric textures. Different from previous research, in this study the authors built a prototype system using wavelet Haar and backpropagation to recognize Tais Timor Leste motif which is a local heritage rich with philosophical and historical values for the people of Timor Leste.

II. LITERATURE REVIEW

A. Wavelet

The wavelet transform is a process of converting data into another form in order to be more easily analyzed. This process is widely used in the process of decomposing, detection, recognition of images. Yang et al. [6] in their research, had been using wavelet energy and biogeography-based optimization in automatic classification of images of the brain. Orozco et al. [7] in research used wavelet descriptor and support of vector machines to classify modular system in the lungs. The further research by Yektaii et al. [8] showed that they could use wavelet compression in preserving classifiability for digital images. Another study conducted by Raja and Gangatharan [9] showed in their research how to use wavelet packet decomposition of correct corresponding sub-band in the decomposition of automated diagnosis of glaucoma. While the research conducted by Bozkurt et al. [10] used complex wavelet transform to classify letters and calligraphic style.

B. Backpropagation

Backpropagation algorithm has been successfully applied in various research fields such as pattern recognition, identification, classification, analysis, predictions and many more. There were some related studies like the one

978-1-4673-9899-2 /17 $31.00 © 2017 IEEE

DOI 10.1109/ICSIIT.2017.11

conducted by Wang and Ma [11] who used backpropagation neural network to predict the wheat stripe rust. Another study was conducted by Wu et al. [12] with their momentum backpropagation algorithm for the identification of low resistivity pay zones in the sandstone. Al-Abadi [13] was using backpropagation of imitated neural network on stage-discharge modeling relationship to the Gharraf River of Southern Iraq. Lahmiri [14] applied backpropagation algorithm in predicting finance. More intensive search was conducted by Kosbatwar and Pathan [15] who applied backpropagation algorithm with neural network approach in pattern association for character recognition. Mansour et al. [16] used a backpropagation algorithm in neural network for voice recognition. Other research by Chaturvedi [17] was using backpropagation feed forward network for rainfall prediction. Tikoo and Malik [18] deep in their journal used Viola Jones and backpropagation neural network for face recognition.

III. METHODS

A. Discrete Wavelet Transform

Transformation is the process of converting data into another form so it is easy to analyze. Wavelet is a small wave that has the ability to group and the image energy is concentrated on a small group of coefficients, while the other coefficients contain a small amount of energy that can be eliminated without reducing the value of the information. The wavelet transformation is one option to extract better features [19]. Haar wavelet is the oldest and simplest wavelet discovered in 1909. Wavelet type is known as mother wavelet or mother wavelet used since the first time intensive. Mother wavelet is defined as follows:

$$\psi(t) = \begin{cases} 1 & 0 \le t < \frac{1}{2}, \\ -1 & \frac{1}{2} \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

$$\phi(t) = \begin{cases} 1 & 0 \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

Haar wavelet is included in the category of orthogonal because the Haar wavelet is equal to db1 wavelet (Daubechies order 1). Haar wavelet filter length is 2. The scaling function of Haar wavelet is shown in Fig. 1.

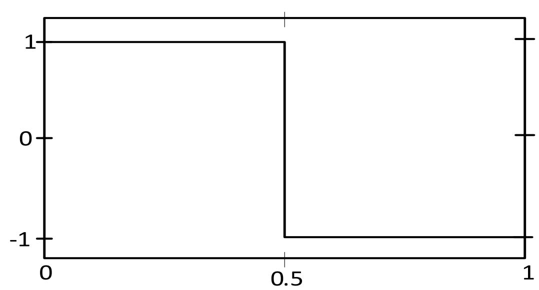

Figure 1. Scaling function of wavelet Haar

The results of this screening are four image subfields from the original image. The four subfields of this image are within the wavelet. The four image subfields are low pass - low pass filter (LL), low pass - high pass filter (LH), high pass - low pass filter (HL), and high pass - high pass filter (HH). This process is called decomposition. Decomposition can be resumed with the image of low pass - low pass filter as input to get the next stage of decomposition. The image below shows an image of the decomposition of level 1 to level 3.

Figure 2. Decomposition of level 1-3

The algorithm used in the Haar wavelet is as follows:

1. Input: image that has been normalized
2. For each of the horizontal and vertical decomposition, determine the coefficient of Low-Pass Filter (LPF) and High-Pass Filter (HPF) with the following functions:

$$\text{LPF}: \; f_k' = \frac{1}{\sqrt{2}}(f_{2k} + f_{2k-1})$$

$$\text{HPF}: \; f_k^* = \frac{1}{\sqrt{2}}(f_{2k} - f_{2k-1})$$

3. Perform repeatedly on approximation coefficients obtained prior to the desired level.

B. Backpropagation Algorithm

Backpropagation algorithm is the algorithm that works by calculating the error between the network output and the target value accordingly. This deployment is done by backwards calculation through the network to update the weights [13]. Backpropagation algorithm performs two first computing stages that are feed-forward computation and backward calculation, where on each of the iterations, the network will improve the values of the weights and biases on all neurons in the network. It is also one of the algorithms using supervised methods (supervised learning) and including multi layer perceptron network [20].

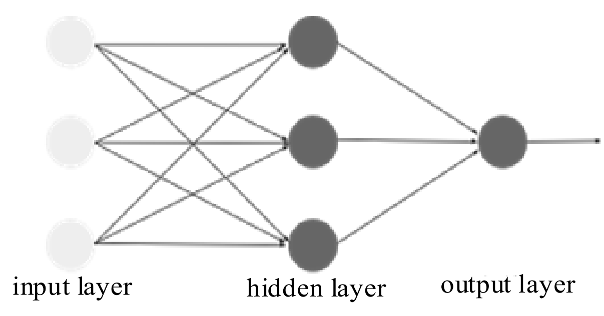

Figure 3. Multi layer perceptron network

Backpropagation learning algorithm:

1. Initialize all inputs, targets, initial weights, initial bias and output targets.
2. Initialize Epoch.
3. Initialize the learning rate, maximum error.

Forward Propagation Stage

1. Each unit of input (X_i, i = 1,2,3, ..., n) receives signals x_i and forwards the signal to all units in the hidden layer.
2. Each hidden unit (Z_j, j = 1,2,3, ..., p) sums up the weighted input signal by the following equation:

$$z\_in_j = b1_j + \sum_{i=1}^{n} x_i v_{ij} \tag{1}$$

and applies the activation function to calculate its output signals:

$$Z_j = f(z\_in_j) \tag{2}$$

where the activation function used is a sigmoid function, and then it sends the signal to all units of output.

3. Each unit of output (Y_k, k = 1,2,3, ..., m) sums up the weighted input signal

$$y\_in_k = b2_k + \sum_{i=1}^{m} x_i v_{ik} \tag{3}$$

and applies the activation function to compute its output signals:

$$Y_k = f(y\_in_k) \tag{4}$$

Backpropagation Stage

1. Each unit of output (Y_k, k = 1,2,3, ..., m) receives a target pattern corresponding to the input pattern of training, then calculates the error with the following equation:

$$\delta_k = (t_k - Y_k) \cdot f'(y\_in_k) \tag{5}$$

f' is the derivative of the activation function then calculate correction weights by the following equation:

$$\Delta w_{jk} = \alpha \cdot \delta_k \cdot Z_j \tag{6}$$

Then, calculate the bias correction by the following equation:

$$\Delta w_{0k} = \alpha \cdot \delta_k \tag{7}$$

as well as submit value δ_k unit to unit in the right most layer.

2. Each hidden unit (Zj, j=1,2,3,...,p) sums up their input delta (from the units that are in the layer on the right side):

$$\delta\_in_j = \sum_{k=1}^{p} \delta_k w_{jk} \tag{8}$$

To calculate the error information, multiply this value by the derivative of the activation function:

$$\delta_j = \delta\_in_j \cdot f'(z\_in_j) \tag{9}$$

After that, calculate the weighted correction with the following equation:

$$\Delta v_{ij} = \alpha \cdot \delta_j \cdot x_i \tag{10}$$

After that, calculate the biased correction with the following equation:

$$\Delta v_{0j} = \alpha \cdot \delta_j \tag{11}$$

Weight and Bias Change Stage

1. Each unit of output (Y_k, k = 1,2,3, ..., m) is to amend the weights and biases change (j = 0,1,2, ..., p) by the following equation:

$$w_{jk}(\text{new}) = w_{jk}(\text{old}) + \Delta w_{jk} \tag{12}$$

Each hidden unit (Z_j, j = 1,2,3, ..., p) to amend the weights and biases (i = 0,1,2, ..., n) by the following equation:

$$v_{ij}(\text{new}) = v_{ij}(\text{old}) + \Delta v_{ij} \tag{13}$$

2. Testing the stopped condition.

IV. Discussion and Result

The process of Tais Timor Leste motif recognition uses wavelet transformation and backpropagation algorithms and the ordering process can be seen in Fig. 4.

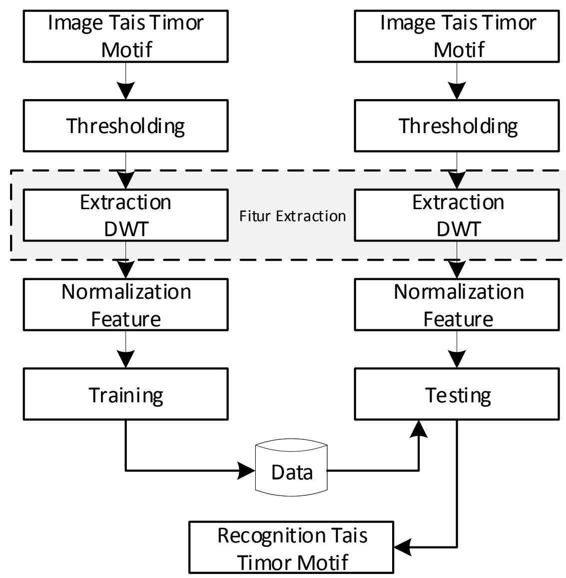

Figure 4. A flow diagram of Tais Timor motif recognition

A. *Dataset*

Tais Timor Leste image motif used in this study was obtained from the office of secretary of state for arts and cultural affairs of Timor Leste. Here are a few samples of Tais Timor Leste motif images before processing, as seen on Fig. 5.

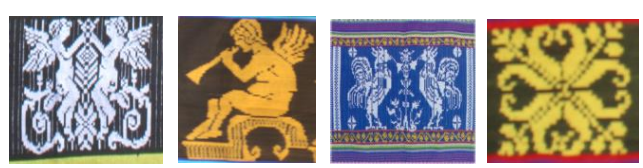

Figure 5. Motif image before processing

B. *Image Processing Stages*

Image type motif used in this study is jpg and bmp extension, which has been cropped out of the image manually by the researchers of Tais Timor Leste. Color image is converted to grayscale. Feature values are extracted from the image, and then normalized for training and testing processes with the backpropagation algorithm.

C. *Wavelet Haar*

Waveler Haar in this study is used to perform the decomposition of any imagery training and test images. The level of decomposition of each image training and test images is a decomposition of level 5. The results of Haar wavelet extraction will be used as an input value in the propagation algorithm.

D. *Feature Extraction*

At this stage feature extraction will be done to the image feature or a motif to obtain information of the object in the image of Tais Timor Leste motif that want to be recognized or distinguished by other objects. Stages of feature extraction in this study consist of pre-processing, Haar wavelet transformation for feature extraction in order to reduce the dimensions of the image of the motif and get the image features.

Stages of feature extraction process on the input image motif can be seen in Fig. 6.

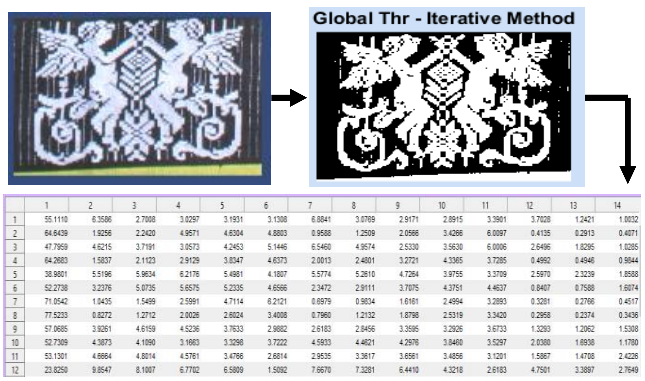

Figure 6. Process of feature extraction on the motif image

E. *Training Stages*

At this stage, training on 18 motif images was done. The stages on feature extraction of this motif image in order to obtain the values of features can be seen in Fig. 7.

Figure 7. Stages menu of training process

F. *Testing Stage*

At this stage values of feature extraction result are used as input value in the backpropagation algorithm to perform the process of recognition of the Tais Timor Leste motif. The stages of the testing process and the recognition of Tais motif image can be seen in Fig. 8.

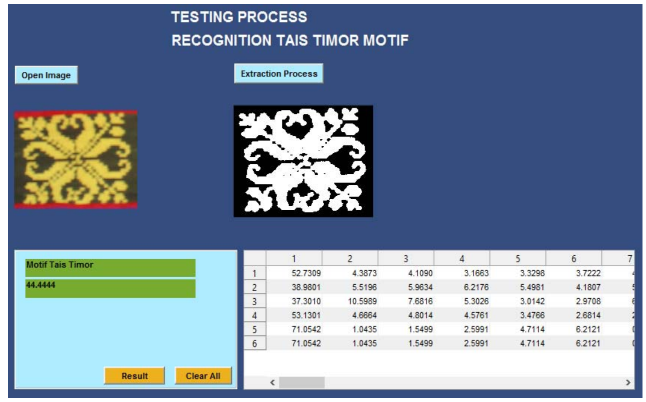

Figure 8. Stages menu of recognition process

In this study, we used 4 different parameter values of neural network with 5 hidden layers and Mean Squared Error (MSE) of 0.01, as can be seen on Table I.

TABLE I. TESTING PARAMETER

Testing Parameter					
No.	**Learning rate**	**Epho**	**Momentum**	**Hidden layer**	**MSE**
1.	0.1	5000	0.5	5	0.01
2.	0.01	10000	0.6	5	0.01
3.	0.001	15000	0.7	5	0.01
4.	0.0001	20000	0.8	5	0.01

This test has been carried out by testing 10 motifs of 18 training images. Tests were performed 40 times with a variety of different test parameters to test images.

TABLE II. RESULTS OF TESTS WITH TEST PARAMETERS: LEARNING RATE 0.1, MAXEPHO 5000, MOMENTUM 0.5

Tais	Learning rate	Max-epho	Momen-tum	MSE	Result
Motif 1	0.1	5000	0.50	0.12075	correct
Motif 2	0.1	5000	0.50	0.15149	correct
Motif 3	0.1	5000	0.50	0.071104	incorrect
Motif 4	0.1	5000	0.50	0.12861	incorrect
Motif 5	0.1	5000	0.50	0.13697	correct
Motif 6	0.1	5000	0.50	0.12878	incorrect
Motif 7	0.1	5000	0.50	0.14655	correct
Motif 8	0.1	5000	0.50	0.151459	correct
Motif 9	0.1	5000	0.50	0.073544	incorrect
Motif 10	0.1	5000	0.50	0.120275	correct

From Table II, it appears that the network is able to identify the motif trained with accuracy and recognition success rate of 60%.

TABLE III. RESULTS OF TESTS WITH TEST PARAMETERS: LEARNING RATE 0.01, MAXEPHO 10000, MOMENTUM 0.6

Tais	Learning rate	Max-epho	Momen -tum	MSE	Result
Motif 1	0.01	10000	0.60	0.0085515	correct
Motif 2	0.01	10000	0.60	0.0099764	correct
Motif 3	0.01	10000	0.60	0.0099002	correct
Motif 4	0.01	10000	0.60	0.009969	correct
Motif 5	0.01	10000	0.60	0.0099875	incorrect
Motif 6	0.01	10000	0.60	0.0099772	correct
Motif 7	0.01	10000	0.60	0.0099885	incorrect
Motif 8	0.01	10000	0.60	0.0096516	correct
Motif 9	0.01	10000	0.60	0.0099856	correct
Motif 10	0.01	10000	0.60	0.0099435	correct

From Table III, it appears that the network is able to identify the motif trained with accuracy and recognition success rate of 80%.

TABLE IV. RESULTS OF TESTS WITH TEST PARAMETERS: LEARNING RATE 0.001, MAXEPHO 15000, MOMENTUM 0.7

Tais	Learning rate	Max-epho	Momen -tum	MSE	Result
Motif 1	0.001	15000	0.70	0.0099996	correct
Motif 2	0.001	15000	0.70	0.0099955	incorrect
Motif 3	0.001	15000	0.70	0.0099989	correct
Motif 4	0.001	15000	0.70	0.009998	incorrect
Motif 5	0.001	15000	0.70	0.009993	correct
Motif 6	0.001	15000	0.70	0.0099985	correct
Motif 7	0.001	15000	0.70	0.0099998	incorrect
Motif 8	0.001	15000	0.70	0.0099939	correct
Motif 9	0.001	15000	0.70	0.0099986	correct
Motif 10	0.001	15000	0.70	0.0099945	incorrect

From Table IV, it can be seen that the trained network is able to recognize patterns with accuracy and recognition success rate of 60%.

From Table V, it appears that the network is able to identify the motif trained with accuracy and recognition success rate of 80%.

TABLE V. RESULTS OF TESTS WITH TEST PARAMETERS: LEARNING RATE 0.0001, MAXEPHO 20000, MOMENTUM 0.8

Tais	Learning rate	Max-epho	Momen -tum	MSE	Result
Motif 1	0.0001	20000	0.80	0.0099999	correct
Motif 2	0.0001	20000	0.80	0.0099979	incorrect
Motif 3	0.0001	20000	0.80	0.0099998	correct
Motif 4	0.0001	20000	0.80	0.0099996	correct
Motif 5	0.0001	20000	0.80	0.0099995	correct
Motif 6	0.0001	20000	0.80	0.0099997	correct
Motif 7	0.0001	20000	0.80	0.009998	correct
Motif 8	0.0001	20000	0.80	0.0099997	correct
Motif 9	0.0001	20000	0.80	0.0099998	correct
Motif 10	0.0001	20000	0.80	0.0099968	incorrect

From Table VI, the results show that different parameters of backpropagation network performance are able to identify the motif with the best accuracy of 80%, which was achieved with learning rate 0.01, Maxepho 10000, and momentum 0.60.

TABLE VI. RESULTS OF TESTS WITH FOUR DIFFERENT PARAMETERS TESTING

Testing Paramater Result			
Learning rate	Epho	Momentum	Recognition
0.1	5000	0.5	60%
0.01	10000	0.6	80%
0.001	15000	0.7	60%
0.0001	20000	0.8	80%

V. CONCLUSION

Based on the analysis and discussion, we can draw a number of conclusions, which are as follows:

- The recognition of motif image of Tais Timor based on wavelet transformation and back propagation algorithms give good results, which are proven by 80% of recognition success rate that is obtained in relatively short time of recognition.
- Haar wavelet transformation is best used as an initial process for extracting motif image features. The backpropagation algorithm is used as the recognition element in identifying Tais Timor Leste motif. So it can be developed for the recognition of motif data in real time.

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