Advanced Integrative Thermography in Identification of Human Elevated Temperature

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Abstract: - Thermography is a non-invasive and non-contact imaging technique used widely in the medical arena. This paper investigates the analysis of thermograms with the use of Artificial Neural Networks (ANN) and Bio-statistical methods. It is desired that through these novel approaches, accurate detection using thermography technique can be achieved. The proposed method is a multi-pronged approach comprising of Regression, Radial Basis Function Network (RBFN) and Receiver Operating Characteristics (ROC) Analysis. It is a novel and combined technique that can be used to analyze complicated and massive numerical data. This integrative technique is used to analyze temperature data extracted from febrile thermograms. Through the use of ANN and Bio-statistical methods, advances are made in thermography application with regard to achieving a higher level of consistency. This allows us to have in place a reliable contactless system for mass screening of fever subjects, which enable us to differentiate febrile from non-febrile cases in as short time as possible.

Key-Words: - Thermography, Advanced integrative assessment, Elevated temperature, Infrared

1 Introduction

Thermography is a non-invasive diagnostic method that is economic, quick and does not inflict any pain on the subject. It is a relatively straightforward imaging method that detects the variation of temperature on the surface of the human skin. Thermography is widely used in the medical arena [1-27]. This includes the detection of elevated body temperature [6-27], which is the focus of this paper. Thermograms alone will not be sufficient for the medical practitioner to make a diagnosis. Analytical tools like bio-statistical methods and Artificial Neural Network (ANN) such as Radical Basis Function Network (RBFN) is utilized to analyze the thermograms. Figures 1 and 2 show two typical examples of temperature profile non-febrile and febrile thermograms.

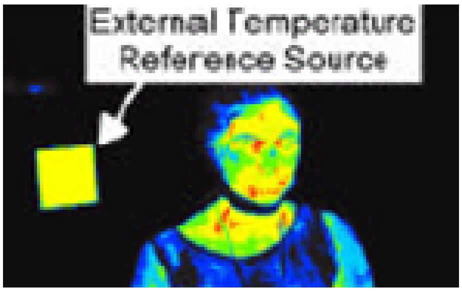

Figure 1: Non-Febrile Thermogram (©CEO)
(body temp. by oral thermometer of 36.5^{o}C)

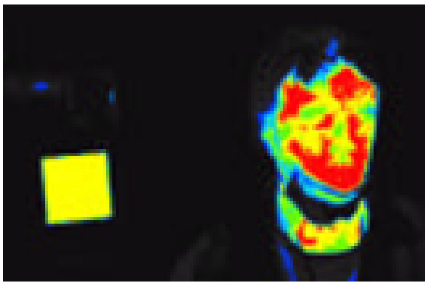

Figure 2: Febrile Thermogram (©CEO)
(body temp. by oral thermometer of 38.6^{o}C)

Neural network is a pattern recognition program that has the ability to predict the outcome based on the various inputs fed into the program. For elevated body temperature thermography, the program will predict if the subject is febrile or non-febrile.

2 Problem Formulation

Lately, the WHO is urging the world to brace for a 2nd wave of the H1N1 pandemic as the heavily-populated northern hemisphere edges towards the cooler season when flu thrives. There had been 2nd and 3rd waves in previous pandemics. One would thus need to be prepared for whatever surprises this capricious new virus delivers next. More than 6000 people have died since H1N1 was uncovered in Mexico nearly seven months ago (Apr.-mid-Oct. 09). Twenty-two million

Americans were infected by the H1N1 during the above period of which 4000 were killed after a new counting method yielded an estimate six times higher than the last one. The virus is more infectious than seasonal flu and more durable through warmer months. It is mystified at the 'most worrying' characteristic of this virus. Nearly 40% of the most severe or fatal cases occur in people who are in perfect health.

Fever has been regarded as an important symptom of pandemic influenza though a recent research reveals that one in five of the H1N1 or swine flu pandemic won't be detected, some have mild or no fever, and their general symptoms make identifying them hard and still pass on the virus. It was reported lately that only half had high fevers of 37.8 deg C or more - one of the symptoms the United States uses to identify H1N1 cases. If we use this cut-off, then 46% of confirmed cases would not have been picked up. Cough was the most common symptom; affecting four in five patients, although only half had sore throats. For most H1N1, the fever receded a day after they started taking Tamiflu. Doctors thus do not know whether the virus is alive or dead - so they are uncertain if the person is still infectious. However, improvement in accuracy of using non-contact IR system to detect feverish subjects is useful for other flu pandemics like SARS and H5N1.

3 Problem Solution: Designed integrated approach

There are many well documented articles including comprehensive review papers in good journals [7,11,12,16,18,21,22,24,26] as well as recent ISO procedures and standards, (ISO/TR 13154 & IEC 80601-2-59) as published recently [27] that are closely related to the present topic. These standards are related to "Deployment, implementation and operational guidelines for identifying febrile humans using a screening thermograph" and "Particular requirements for the basic safety and essential performance of screening thermographs for human febrile temperature screening".

To enhance the performance of ANN RBFN, a bio-statistical method – Parabolic Regression (PR) is incorporated to increase the accuracy of the results. Selecting only useful and relevant inputs, which are used to predict the outcome, does this. This way, the diagnosis is proved to be more accurate and reliable.

The proposed approach is a multi-pronged approach that comprises of PR, RBFN and ROC analysis. Table 1 shows the software needed for all the processes. Figure 3 presents the entire process in a flow chart, including the steps prior to Advanced Integrated Technique (AIT).

Step 1: Parabolic Regression (PR)

PR reflects the correlation between the variables and the actual health status (febrile or non-febrile) of the subject, which is decided by means of a thermometer placed in the ear. The output is either 1 or 0, corresponding to febrile and non-febrile cases respectively. The two input variables with the best correlation are chosen. The rationale behind using PR over Linear Regression (LR) is the PR offers a more accurate and realistic approach in providing the correlation coefficient. The following temperature data was collected [22]: minimum/maximum/average temperature of forehead region; standard deviation of forehead region; minimum/maximum/average temperature of near eye region, and, standard deviation of near eye region.

Step 2: ANN RBFN

Based on the various inputs fed into the network, RBFN is trained to produce the desired outcome, which are either positive (1) for febrile cases and (0) non-febrile cases [25]. When this is done, the RBFN algorithm will possess the ability to predict the outcome when there are new input variables. The advantages of using RBFN include fast learning, superior classification and decision-making abilities as compared to other networks such as back propagation (BP) [23].

Step 3: ROC Analysis

ROC is used to evaluate the accuracy, sensitivity and specificity of the outcome of RBFN Test files. In other words, it is used to evaluate if the RBFN is well built or not.

Table 1: Summary of software used for AIT

Purpose	Software
View thermograms from thermal imager & extract temperature data	Image J
Normalize raw temperature data Perform statistical analysis (e.g. mean, median, std dev)	MS Excel Statistical Toolbox
Determine the correlation of each variable with the output (health status)	MedCal
Training and testing of data. Building an algorithm for the data	NeuralWorks ProII (UK OU)
To evaluate the effectiveness of the computed method	MedCal

The 2nd and 3rd columns in Table 2 show the results for PR and LR. The PR coefficient of determination is always higher than LR coefficient of determination in 'fitting the data' or providing the correlation function. The *maximum temperature of eye region* and *maximum temperature of forehead region* allow the best correlated spots on the frontal face with regard to the core temperature. They are used as input variables for the training of ANN.

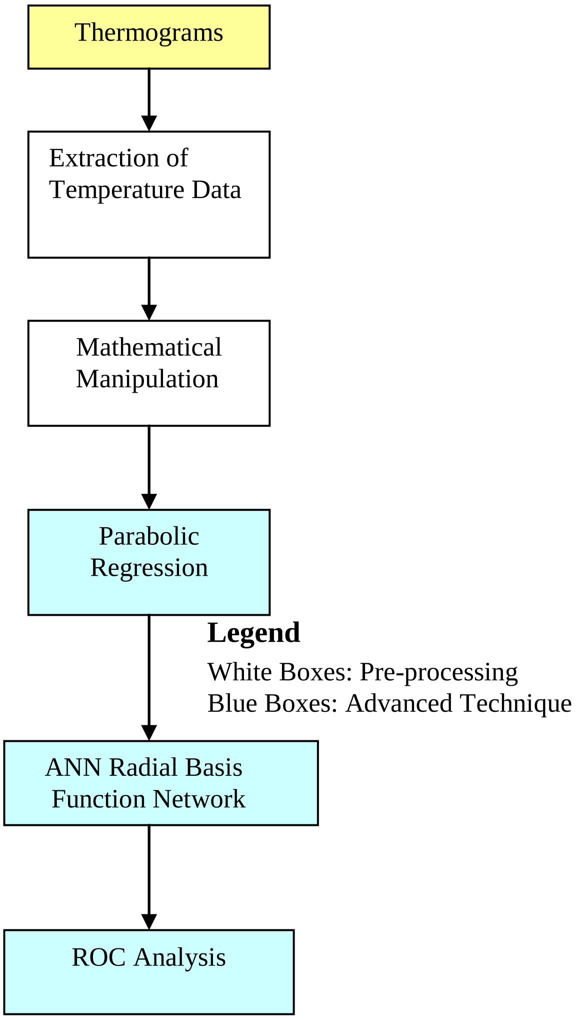

Figure 3: Flow Chart of AIT for Febrile & Non-Febrile Subjects.

Table 2: Summarized results for Step 1 of AIT for febrile and non-febrile thermograms.

Independent variable	Coeff. of determination (LINEAR)	Coeff. of determination (PARABOLIC)
Max Temp at Eye Range	0.5507	0.6315
Min Temp at Eye Range	0.0672	0.1114
Std Dev at Eye Range	0.0303	0.0588
Total Ave. at Eye Range	0.4489	0.5721
Max Temp at Forehead Range	0.4973	0.6362
Min Temp at Forehead Range	0.1169	0.1798
Std Dev at Forehead Range	0.0053	0.0053
Total Ave. at Forehead Range	0.3759	0.5379

Various combinations of Learn Rule (Delta, Norm-cum-Delta, Ext DBD), Transfer Rule (Sigmoid, DNNA, Linear, TanH, Sine) and Options (Connect Prior, Connect Bias etc.) were tested. With the inclusion of Options (Table 3), more NNs with an accuracy of 96% are generated. It is found that the RBFN is credible and has the ability to differentiate febrile from non-febrile cases to a very large extent.

In many ANN RBFN models that are built, an accuracy rate of 96% is achieved. It was interesting to note that there are always four input data which the model always predicts wrongly and accounts for the 4% error. This is due to inconsistencies between the patient's facial temperature (deduced from the thermograms) and his/her core temperature. For example, the Max Temp in the near eye region and Max Temp in the forehead region are very high and it indicates the fact that the person is having fever. Hence, ANN predicts that the person is having a fever. However, the core temperature taken by the thermometer suggests that the person is not having fever. Thus, ANN's prediction is wrong. This is certainly not the ANN's fault because in these cases, the person's facial temperature has poor correlation with his core temperature. Without these exceptional cases, ANN should achieve an even higher accuracy rate.

Table 3 shows that the RBFNs are well built. The area under curve for all the RBFNs is larger than 0.97. These RBFNs have high sensitivities (> 90%) and high specificities (> 80%). This suggests that the overall diagnostic performance is reliable and can be used for mass screening of febrile subjects. The best performing RBFN is a Single Layered Perceptron (SLP) with Ext DBD as the Learn Rule, Linear Function as the Transfer Rule and MinMax Table as the selected Option. The area under the ROC curve is 0.984. Its sensitivity is 100% and its specificity is 94.3%.

4 Conclusion

Through the use of ANN and Bio-statistical methods, progress is made in thermography application with regard to achieving a higher level of consistency. This is made possible with the introduction of the novel AIT in thermogram analysis. The AIT has a high level of accuracy rate in prediction based on the temperature data extracted from the thermograms. For elevated body temperature thermography, the AIT enables us to have in place a reliable system for mass screening for fever cases. It has been shown in this paper that the integrative approach (PR + ANN + ROC) has surpassed the conventional bio-statistical approach (LR + ROC) [23], which was used for analytical purposes during the SARS outbreak in 2003. In other words, the AIT enables us to differentiate febrile from non-febrile cases in as short time as possible. This is important in view of the SARs outbreak and the potentially lethal Avian flu or malaria. In the event of such a virus outbreak, we will be better prepared to handle the situation.

To sum it up, thermography application is like an unpolished gemstone, waiting for us to unlash its full potential. The future development of an integrative fever screening system may incorporate the effectiveness of Laser Doppler Flowmeter (for heart rate), microwave radar (for respiration rate) and thermography (for skin temperature) to eliminate setbacks or noises that are prevalent in each individual device. All the medical images/data obtainable from these screening devices can then be supplied into the self-developed software that is build based on ANN. With sufficient data collected from affected patients, the software can be trained to carry out automatic feature definition and image classification objectively. Since the system is non-invasive and contactless, it shall allow for a fast, effective medical treatment and diseases diagnostic and thus prevent secondary exposure of quarantine doctors and officers to toxins and infectious organisms.

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Table 3: ROC results for RBFN SLP with selected combination of Learn Rule & Transfer Rule (with various Options tested)

Learn Rule	Transfer Rule	Option	Score (%)	Area Under Curve	Sensitivity	Specificity
Delta Rule	Sigmoid	Connect Prior	96	0.972	100	84.1
Delta Rule	Sigmoid	MinMax Table	96	0.974	91.7	94.3
Delta Rule	DNNA	Connect Prior	96	0.971	91.7	94.3
Delta Rule	DNNA	Linear O/P	96	0.971	91.7	94.3
Delta Rule	DNNA	Softmax O/P	96	0.971	91.7	94.3
Delta Rule	DNNA	Connect Bias	96	0.970	91.7	94.3
Norm-Cum-Delta	TanH	Connect Bias	96	0.973	91.7	94.3
Norm-Cum-Delta	TanH	MinMax Table	96	0.978	100	87.5
Norm-Cum-Delta	Sigmoid	Connect Prior	96	0.975	100	88.6
Norm-Cum-Delta	Sigmoid	Linear O/P	96	0.975	100	88.6
Norm-Cum-Delta	Sigmoid	Connect Bias	96	0.970	100	85.2
Norm-Cum-Delta	Sigmoid	MinMax Table	96	0.981	100	94.3
Norm-Cum-Delta	Sine	Connect Bias	96	0.975	91.7	94.3
Norm-Cum-Delta	Sine	MinMax Table	96	0.975	91.7	94.3
Ext DBD	Linear	Connect Bias	96	0.980	100	93.2
Ext DBD	Linear	MinMax Table	96	0.984	100	94.3

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