

Machine Learning Optimization for Colour Image Reconstruction from Thermal/Infrared Images

WTVL Gunarathne¹ and DMR Kulasekara²

¹ General Sir John Kotelawala Defence University, Sri Lanka

#Corresponding author; vgunarathne@gmail.com

Abstract— Machine Learning has generated a tremendous interest in research and development under the umbrella of Artificial Intelligence. It was a field that evolved from pattern recognition and computational learning in Artificial Intelligence. Machine Learning algorithms are capable of identifying how to accomplish certain tasks by generalizing from real world examples. In comparison to manual programming, this is often feasible and cost-effective. In this context, this paper focuses on the use of these optimized machine learning algorithms in order to reconstruct colour images from thermal/infrared images. With the capability of these machine learning algorithms to identify patterns in existing data sets, such an algorithm can be used to reconstruct a colour images based on the features that are given to the algorithm. Most night time photography uses thermal imagery because of its capability of capturing thermal radiation from the human body. So these data can be used to reconstruct a colour image based in feature recognition form the thermal image. In conclusively it is our intention to use the power of machine learning techniques to build a system that can generate colour images by analysing the small amount of details that are present in thermal images.

Keywords— Thermal Imagery, Facial Image reconstruction, Machine Learning

I. INTRODUCTION

Machine learning field and machine learning algorithms have gained immense popularity due to its capability of improving itself through experience[1]. It has become one of the most growing technical fields being nurtured by a mix of computer science, data science, statistics and artificial intelligence. Machine learning algorithms are capable of identifying patterns and how to accomplish certain tasks by generalizing from the real world examples. It all depends on the amount of data that is being fed to the algorithms. More problems can be tackled as more and more data is available. This is one of the interesting adoptive properties of machine learning algorithms. This is often feasible and cost effective. Machine learning is used in Web search, spam filters,

stock trading, recommender systems, fraud detection, ad placement, credit scoring, drug design, and many other applications.[2] Under the umbrella of Artificial Intelligence, machine learning has flourished as the method of developing systems such as speech recognition, natural language processing, robot control, computer vision and many other things. Training a system with examples of desired input-output behaviour has become more feasible than to program and algorithm to anticipate a desired output based on all possible inputs. Machine learning algorithms can be used to tackle learning problems. Learning problems can be defined as an improvement of the threshold of performance when executing a task over and over again and there by learning from it. For example, a machine learning algorithm trained to differentiate between male and female faces which will flag a given image, whether the person is a male or a female, will improve its performance over time when encountering more and more data sets and through processes such as active learning.[3]

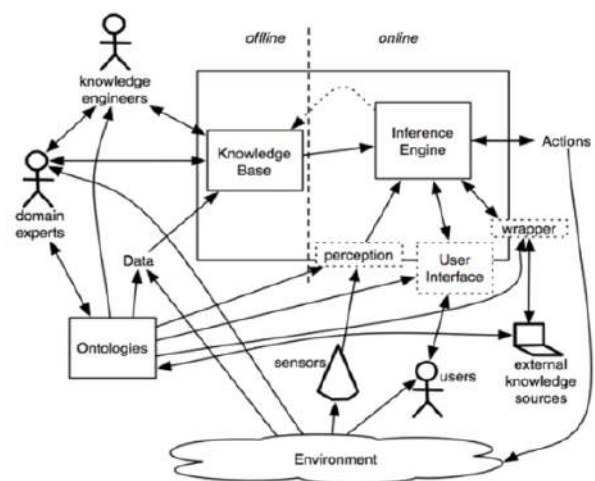


Figure 1 Machine Learning Mechanism

The focus of this paper is the use of these machine learning techniques to understand the minute details of the face image data from thermal images of human faces and using the machine learning optimization to build a colour image model of the face. When the thermal image is submitted to the algorithm, it will analyse for the features of the image and based on the

existing knowledge base that it has, it will reconstruct a face based on the data. Thermograms are the images that are generated by detecting radiation in the long infrared range of the electromagnetic spectrum. A thermal infrared camera is being used for this purpose. Simply said, the camera can identify the heat signatures emitted by any object that is inside its view finder. After pre-processing the thermogram using image processing techniques, certain physiological features can be extracted based on the blood perfusion data. Blood perfusion data are based on the way that blood vessels are distributed under the skin. Distribution of blood vessels is unique for each individual and a set of extracted minutiae points from a blood perfusion data of a human face would be unique for that face. So these unique features will assist in reconstructing the facial data and finally output a facial image of a person.

II. EXISTING SYSTEMS

Biometrics is a Greek origin word meaning measure of life. It means that the measures or the metrics that we take of the human beings. Facial data analysis is a part of this field. Biometrics use various physical characteristics to match with the data in the database.

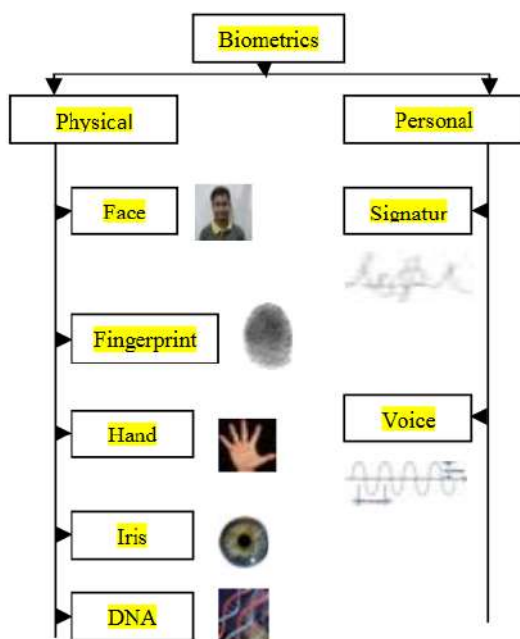


Figure 2 Biometric uses

Abundantly used physical biometrics are fingerprints, facial features, hand geometry and eye features etc. Among these many biometric measures, facial detections are a significant trait that is being used in the modern world. One significant importance is that no physical interaction is needed for facial images to be used. The system can capture the facial image of a person while a person is walking through a door or while he is standing, there by revoking the requirement for the individual to touch a panel, keep a fingerprint or any other physical interaction. In comparison of visual images with thermal images, the visual images have a higher preference in many aspects. Following can be considered as a few set of advantages of visual images.

- Location and extraction of features can be done easily.
- Optical cameras are less expensive.

But factors like illuminations and viewing directions have a noteworthy impact on these visual images[4]. One solution to overcome these limitations is using 3D data obtained from 3D vision devices. They are less independent on illuminations but the downside to it is the massive cost. So a simple, feasible solution to this would be infrared or thermal images which do not depend on illuminations and other factors. Colour which comprises the longest wavelength of the visual spectrum is red. "Infra" which means below in Latin suggests that Infrared is below Red.

The wavelengths of different IR spectrums are shown in the following table[5].

Spectrum	Wavelength Range
Near-Infrared (NIR)	0.7-1.0 μm
Short-wave Infrared (SWIR)	1-3 μm
Mid-wave Infrared (MWIR)	3-5 μm
Thermal Infrared (TIR)	8-14 μm

Figure 3 Wavelength changes for different IR Spectrums

Following mentioned advantages can be obtained from using thermal imaging.

- The cost of IR cameras has been reduced recently due to the implementation of CCD (Charged Coupled Device) technology[6].
- Different lighting conditions doesn't affect thermal imaging, even complete darkness.
- IR face images contains details about the basic anatomical information about the face.
- Facial detections, localizations and segmentations are much easier.

- Has much better accuracy because it uses facial temperature variations.

In relevance to current thermal imaging systems, they can be classified into three main parts namely, image acquisition, image processing and classification.

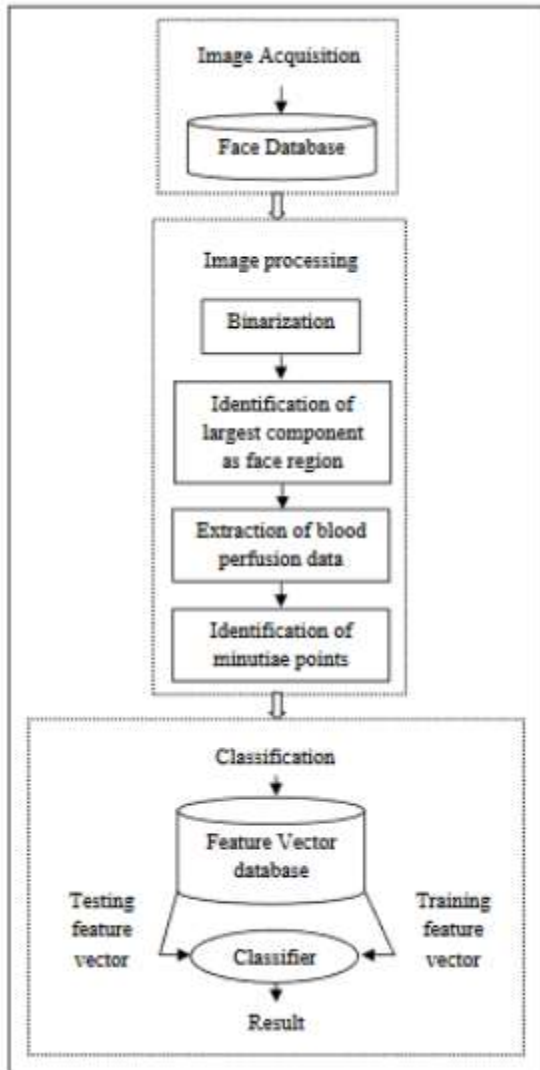


Figure 4 Block diagram of a present system

III. TECHNOLOGIES USED

There can be various scenarios where visual images become un-resourceful and are incapable of meeting out certain requirements. Specially for night time surveillance imagery, acquisition of visible light images is a bit difficult due to the lack of visible light. This is the place where thermal imagery plays a major role. Thermal imaging which uses mid-wave or long-wave infrared radiations which are naturally emitted by the human body can be utilized to overcome the shortcomings of visual images. The drawback here is that thermal images lack the wealth of information

that is available in visual images and hence it is difficult to identify features like facial cues in a thermal image to recognize a person. So this section focusses on the technologies that are used to develop a system that uses machine learning algorithms to study features that are common to visual and thermal images from a set of data and try to reconstruct a visual image of a face from a given thermal image. Matching thermal face imagery to the existing databases of facial images therefore requires the development of across modality face recognition algorithms and methods.

Due to the gap caused by the wavelength difference between visible radiation and thermal radiation, thermal to visual face reconstruction can be challenging. The existing systems[4], [7], [8] sectioned detailed about the usage of NIR images vs visual images for facial recognition. Details about the NIR-to-visible[9] face recognition and the SWIR-to-visible[10] face recognition was also briefly described. Since both NIR and SWIR require active illumination it is not very practical to night time surveillances.

The key point in solving the thermal-to-visible imaging drawback is the development of an algorithm or transform space that well-correlates the thermal and visible face signatures.

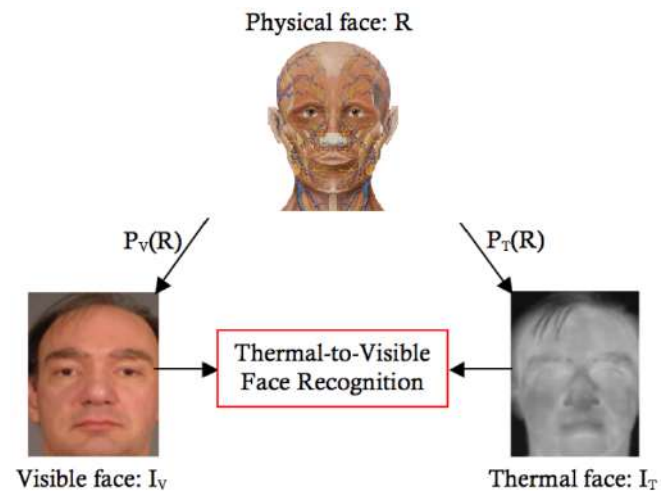


Figure 5 Illustration of visible and thermal representations of the physical face

Here our main focus is the matching of thermal images to visual images so that the machine learning algorithm can be trained to analyse and detect patterns between the two image domains. We convert this face identification problem of matching thermal images to visible images as a multi-modal face recognition problem. Before tackling this, various

pre-processing techniques such as self-quotient[11] images, difference-of-Gaussian[12] filtering and various feature transforms are being used.

A. PRE-PROCESSING

Due to the different signatures that thermal and visual images contain, pre-processing is essential in finding a solution to the problem. Pre-processing consists of two main stages. Namely,

- Thermal image normalization, and
- Local variation reduction for thermal and visible imagery

Simple median filtering prior to image normalization is used to remove the dead pixels within the thermal images.

Step 01: Normalizing thermal signatures

Normalize the thermal signatures by its mean and standard deviation to reduce the temperature offset and statistical variation across thermal images.



Figure 6 Original Image



Figure 7 Normalized Image

Step 02: Adjusts the thermal and visible imagery for local variations.

For visible imagery, illumination primarily induces the local variations, whereas for the thermal imagery, the varying heat distribution within the face produces the local variations. Self-quotient image and difference of Gaussian

Filtering is commonly applied to reduce illumination variations in visible face imagery.

B. FEATURE TRANSFORMS

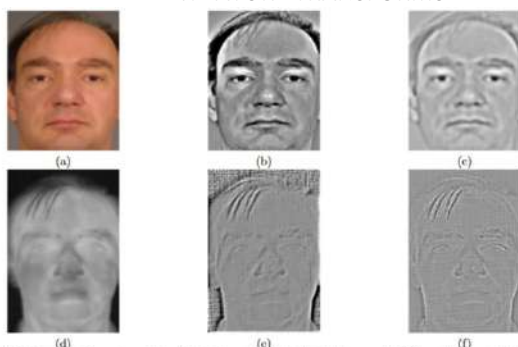


Figure 3. Effect of Pre-Processing of Local Variations. (a) Original visible image (b) SQI applied to visible image (c) DOG filter applied to visible image (d) Original thermal image (e) SQI applied to thermal image (f) DOG filter applied to thermal image

Computer vision applications is crucially dependant on the selection of good features. There are many feature descriptors available to facilitate face recognition. Local Binary Patterns (LBP) is a popular texture and a successful feature descriptor under local illumination variances. LBP are compact and can be easily compared by various histogram metrics. The most popular extension is multi-scale LBP (MSLBP) descriptor.

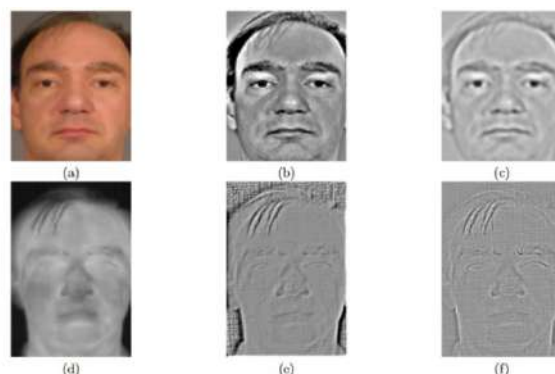


Figure 3. Effect of Pre-Processing of Local Variations. (a) Original visible image (b) SQI applied to visible image (c) DOG filter applied to visible image (d) Original thermal image (e) SQI applied to thermal image (f) DOG filter applied to thermal image

The above figure shows two pre-processed images along with the original images in the visible and thermal domains. As can be observed, SQI emphasizes the edge information in the thermal imagery while DOG filtering blurs the visible imagery. The Gabor wavelets are also effective face descriptors which capture global shape information centred on a pixel. The convolution of multiple Gaussian-like kernels at different scales and orientations captures information insensitive to expression variation and blur at a pixel's location. We consider all these features for thermal-to-visible face recognition. We also compare the results of using raw intensity values as a feature as in some previous works.

IV. DISCUSSION

Performing basic pre-processing consisting of dead pixel removal, affinely warping the face by four fiducial points (two eyes, nose tip, mouth), cropping to face regions, and resizing to 80x100 pixels gives a much better way to generate visual images from thermal images. All these techniques gave a proper insight as to how the task of thermal image reconstruction should be accomplished.

V. CONCLUSION

In this study, I have investigated the thermal-to-visual image reconstruction. The novel combination of pre-processing, feature transforming and PLS-DA recognition framework gives promising results with a

high accuracy. A data set of these visual images and their corresponding thermal images can be fed into a machine learning algorithm which can be trained to analyse the patterns between those image pairs. Thus, that algorithm will be able to generate a new visual image for a thermal image that is provided. In conclusion these techniques can be used to implement a machine learning algorithm that can reconstruct a visual image based on the thermal image that is being provided to the algorithm.

REFERENCES

- [1] E. Horvitz and D. Mulligan, "Data, privacy, and the greater good," *Science*, vol. 349, no. 6245, pp. 253–255, 2015.
- [2] P. Domingos, "A few useful things to know about machine learning," *Commun. ACM*, vol. 55, no. 10, pp. 78–87, 2012.
- [3] N. Lavesson, Blekinge tekniska högskola, and Department of Systems and Software Engineering, "Evaluation and analysis of supervised learning algorithms and classifiers," Blekinge Institute of Technology, Karlskrona, 2006.
- [4] S. G. Kong, J. Heo, B. R. Abidi, J. Paik, and M. A. Abidi, "Recent advances in visual and infrared face recognition—a review," *Comput. Vis. Image Underst.*, vol. 97, no. 1, pp. 103–135, Jan. 2005.
- [5] Anne Cleary, *Face Recognition without Identification*. INTECH Open Access Publisher, 2011.
- [6] Gang Hua, *Face Recognition by Discriminative Orthogonal Rank-one Tensor Decomposition*. INTECH Open Access Publisher, 2008.
- [7] X. Chen, P. J. Flynn, and K. W. Bowyer, "IR and visible light face recognition," *Comput. Vis. Image Underst.*, vol. 99, no. 3, pp. 332–358, Sep. 2005.
- [8] X. Zou, J. Kittler, and K. Messer, "Face Recognition Using Active Near-IR Illumination.," in *BMVC*, 2005.
- [9] Z. Lei and S. Z. Li, "Coupled spectral regression for matching heterogeneous faces," in *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*, 2009, pp. 1123–1128.
- [10] B. F. Klare and A. K. Jain, "Heterogeneous Face Recognition Using Kernel Prototype Similarities," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 6, pp. 1410–1422, Jun. 2013.
- [11] H. Wang, S. Z. Li, and Y. Wang, "Face recognition under varying lighting conditions using self quotient image," in *Automatic Face and Gesture Recognition, 2004. Proceedings. Sixth IEEE International Conference on*, 2004, pp. 819–824.
- [12] X. Tan and B. Triggs, "Enhanced local texture feature sets for face recognition under difficult lighting conditions," in *International Workshop on*

Analysis and Modeling of Faces and Gestures, 2007, pp. 168–182.

ACKNOWLEDGEMENT

I would like to express my great appreciation to Prof. AS Karunananda for his valuable and constructive suggestions during the planning and development of this research work. His willingness to give his time so generously is very much appreciated. I would also like to thank Mr. DMR Kulasekara for his advice and guidance that helped me to make this possible. I would also like to thank Mr. A Gunasekera and staff of the Department of Computer Science at KDU, for their valuable and precious time, which is generously and highly admired.