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# Near-optimal facial emotion classification using a WiSARD-based weightless system

Leopoldo A.D. Lusquino Filho[1], Felipe M.G. França[1] and Priscila M.V. Lima[2] *

1- PESC/COPPE 2- NCE
Universidade Federal do Rio de Janeiro – Brazil

**Abstract**. The recognition of facial expressions through the use of a WiSARD-based *n*-tuple classifier is explored in this work. The competitiveness of this weightless neural network is tested in the specific challenge of identifying emotions from photos of faces, limited to the six basic emotions described in the seminal work of Ekman and Friesen (1977) on identification of facial expressions. Current state-of-the-art for this problem uses a convolutional neural network (CNN), with accuracy of 100% and 99.6% in the Cohn-Kanade and MMI datasets, respectively, with the proposed WiSARD-based architecture reaching accuracy of 100% and 99.4% in the same datasets.

## 1 Introduction

Being one of the fundamental elements in human relationship, the recognition of emotions has been studied by several areas of scientific knowledge, such as Biology, Psychology and Anthropology. Moreover, human-computer interfaces based on automated facial emotions classification are certainly useful for a variety of applications, such as tutors security systems, forensic investigation, social networking, computer graphics and games. Since much of these systems must operate online, ensuring rapid learning is still a highly desired requirement, and may be indispensable in many cases. It was recently shown that a reasonably complex WiSARD-based neural network, applied to the problem of financial credit analysis, performed orders of magnitude faster in training time when compared to SVM, while keeping itself very competitive w.r.t. accuracy [4]. Although the main goal of this work is to explore the WiSARD weightless model in the tasks of facial emotion classification and facial detection, the generation of prototypes of faces expressing basic emotions through 'mental images' produced via the DRASiW mechanism is also offered.

This paper is organized as follows: Section 2 presents the scope of the research related to classification of emotions, such as an overview of the systems already developed for this purpose and a description of the datasets most popular in this area and that were used in this work. Section 3 presents the fundamental concepts related to the WiSARD model, as well as a description of the system architecture used in this work. A discussion of the experimental results of WiSARD validation in popular datasets, as well as a comparison with current

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state-of-the-art and other relevant results found in the literature, are presented in Section 4. Conclusion and future work are presented in Section 5.

## 2 Facial Emotions Recognition

A watershed in the study of the classification of emotions was the work of Ekman and Friesen (1977) [1], where the possibility of cataloging facially expressed basic emotions that are common to all cultures is discussed. In order to define a quasi-exact approach, using only physiological parameters, the Facial Acting Coding System (FACS) was defined. FACS is based on identification of active muscles in a face, which are mapped into units known as 'Action Units' (AUs). Also, six basic emotions universally expressed by humans were defined: *happiness, sadness, anger, disgust, surprise, fear*, as well as the *neutral* emotion.

A detailed survey on FACS and computational systems based on it was produced by Bettadapura [2] (2012). Recently, systems based on convolutional networks [12] [7], have emerged as state-of-the-art for some of the leading rating datasets of facial emotions. The weightless system reported in this work is validated using the full version of the same datasets: **MMI Facial Expression Database**, produced by Pantic et al. [8], and **Extended Cohn Kanade (CKP)**, developed by the Affect Analysis Group of the University of Pittsburgh [9]. A previous exploration of WiSARD $n$-tuple classifier in facial emotion classification was presented in [15]; very good preliminary results were obtained, but a different WiSARD setup was used over a different dataset, the Taiwanese Facial Expression Image Database – TFEID.

## 3 A Weightless Architecture for Emotion Recognition

### 3.1 WiSARD

WiSARD is an $n$-tuple classifier, composed by class discriminators; each discriminator is a set of $N$ RAM nodes having $n$ address lines each [3]. All discriminators share a structure called 'input retina', from which a pseudo-random mapping of its $N * n$ bits composes the input addresses of all of its RAM nodes. Before training and classification phases, all RAM nodes contents are set to zero. Training of a binary pattern belonging to a given class is done in the following way: for any pattern presented to the input retina, all $N$ addressed memory locations of the corresponding discriminator are set to one. During classification phase, and for any input pattern presented in the input retina, each discriminator produces a response $r$ via a summation of all its $N$ RAM one-bit output lines.

A simple and efficient generalization of the WiSARD was introduced [5] in order to deal with big amounts of input data: instead of a single bit, RAM contents store number of hits during training. During the classification phase, each memory position contributes to increase the score $r$ of its discriminator only if its contents exceeds a threshold $b$, from the following disambiguation procedure called *bleaching*: $b$ is initialized with zero and gradually incremented until there is no tie among discriminators.

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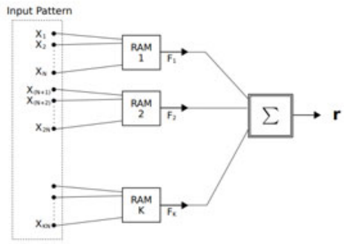


Fig. 1: An example of a WiSARD model discriminator.

An extension to the WiSARD model, called DRASiW [6], is able to use the access rate of the contents of the $N$ RAMs of each discriminator to produce a 'mental image' of what a discriminators has learned into an auxiliary input retina. Note that through this process, one can observe the influence of *bleaching* in the classification phase, by observing how the mental images vary with the increase of $b$.

### 3.2 Face Detection

To extract a face of an input image, a second WiSARD network having a single discriminator trained from manually cut faces is used. Upon being submitted to the network, the image is traversed by a window of 80 × 80 px and the WiSARD selects as a face the image that produces the highest $r$. Alternatively, a trained WiSARD with Local Binary Pattern (LBP) descriptors of faces was also applied.

Fig. 2: Faces detected with a WiSARD $N = 148$, $n = 130$ discriminator.

## 4 Experiments and Discussions

The WiSARD network applied in the recognition of facial emotions used seven (7) discriminators, each one dedicated to one of the seven FACS emotions, with $N = 200$ and $n = 32$. This setup proved to be best for 80 × 80 px binarized images. All input images were pre-processed, being re-sized to have the same proportions (120 × 160 px) and binarized by the Savoula algorithm [10]. Validation was done with automatic face detection using the WiSARD, as described in Section 3.2, and with manually detected faces. The average network training time per image (measured with 10000 images on a computer with an Intel i7 processor, Windows 10) was 0.01s and the classification was 0.07s.

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### 4.1 MMI

All images and videos of this base, which have annotated emotions, were used in the validation. 50 frames were extracted from each video of the base, with the first 15 being associated with 'neutral' emotion and the others with their own annotation. The accuracy obtained was compared with Burket et al. [7] and Wang and Yin [11], who also used the basis for recognition of emotions, rather than their traditional use in detecting Action Units.

| Author | Method | Dataset | Validation | Accuracy (%) |
|---|---|---|---|---|
| Burkert et al. [7] | CNN | Full | 10-fold CV | **99.6** |
| Wang and Yin [11] | LDA | Full | LOO | 93.33 |
| Wang and Yin [11] | QDC | Full | LOO | 92.78 |
| Wang and Yin [11] | NBC | Full | LOO | 85.56 |
| WiSARD (proposed) | AFD | Full | 10-fold CV | **99.3** |
| WiSARD (proposed) | MFD | Full | 10-fold CV | **99.4** |

Table 1: Current state-of-the-art in emotion recognition on the MMI. The WiSARD accuracy was 99.3%, with a standard deviation of 0.1%; AFD: Automatic Face Detection; MFD: Manual Face Detection.

| | Neutral | Happiness | Sadness | Fear | Anger | Disgust | Surprise |
|---|---|---|---|---|---|---|---|
| Neutral | **0.994** | 0.004 | 0.002 | 0 | 0 | 0 | 0 |
| Happiness | 0.016 | **0.973** | 0 | 0 | 0.001 | 0.001 | 0.008 |
| Sadness | 0.002 | 0 | **0.993** | 0 | 0 | 0.004 | 0 |
| Fear | 0.017 | 0 | 0 | **0.979** | 0 | 0 | 0.003 |
| Anger | 0.011 | 0.002 | 0 | 0 | **0.972** | 0.014 | 0 |
| Disgust | 0.008 | 0 | 0 | 0 | 0 | **0.987** | 0.005 |
| Surprise | 0.01 | 0.004 | 0.001 | 0.001 | 0 | 0.004 | **0.976** |

Table 2: The confusion matrix from a 10-fold cross-validation with the WiSARD (AFD) over the MMI dataset.

Most of the misclassified images here are those that are in the transition between the original neutral state and the emotion exhibited in the video from where that frame was taken out, so the emotion has not yet reached sufficient degree of expressiveness.

### 4.2 Extended Cohn-Kanade

All 5876 images with emotion annotations from this dataset were used. The current state-of-the-art [12] for this dataset achieved 100% accuracy, using hand picked images and without cross-validation.

Most of the images erroneously classified in this dataset returned the "neutral" emotion as a result. This occurred almost entirely in images whose face was poorly detected and, therefore, the part of the image selected to represent

| Author | Method | Dataset | Validation | Accuracy (%) |
|---|---|---|---|---|
| Zafer et. al. [12] | NCC | Parcial | LOO | **100** |
| Burkert et al. [7] | NCC | Full | 10-fold CV | 99.6 |
| Happy et al. [13] | SVM | Parcial | 10-fold | 94.09 |
| Kotsia et al. [14] | Multiclass SVM | Full | LOO | 91.6 |
| WiSARD (proposed) | AFD | Full | 10-fold CV | **90.01** |
| WiSARD (proposed) | MFD | Full | 10-fold CV | **100** |

Table 3: The current state-of-the-art in emotion recognition on the CKP. The WiSARD accuracy was 90.01%, with a standard deviation of 0.6%.

| | Neutral | Happiness | Sadness | Fear | Anger | Disgust | Surprise |
|---|---|---|---|---|---|---|---|
| Neutral | **0.927** | 0.012 | 0.013 | 0.005 | 0.019 | 0.009 | 0.012 |
| Happiness | 0.086 | **0.906** | 0.004 | 0 | 0 | 0.002 | 0.001 |
| Sadness | 0.156 | 0.003 | **0.84** | 0 | 0 | 0 | 0 |
| Fear | 0.091 | 0.002 | 0 | **0.891** | 0 | 0.005 | 0.01 |
| Anger | 0.143 | 0 | 0.008 | 0 | **0.841** | 0.003 | 0.001 |
| Disgust | 0.138 | 0.002 | 0 | 0.002 | 0.007 | **0.848** | 0.002 |
| Surprise | 0.109 | 0.001 | 0.001 | 0.004 | 0.001 | 0.004 | **0.88** |

Table 4: The confusion matrix from a 10-fold cross-validation with WiSARD (AFD) over the CKP dataset.

it did not obtain a satisfactory enough score in any discriminator in the classification phase, so gradually the *bleaching* reduced the score of all discriminators to 0, causing the network to return the default classification 'neutral'. When manual face detection was applied, 100% accuracy was achieved. It can be seen that face detection, although a distinct problem, is of crucial relevance for the classification of emotions.

### 4.3 Mental Images

In order to provide qualitative results of WiSARD's learning capabilities using the MMI dataset, mental images of the basic facial emotions were generated. It is possible to observe some representative expressive contours of the emotions learned by the respective discriminators, as well as AUs that explain the reason for erroneous classifications (for example, the clear presence of AU 2 found only in the 'fear' and 'surprise' emotions, in the mental image generated by the discriminator 'disgust').

Fig. 3: Mental images for Neutral, Happiness, Sadness, Fear, Anger, Disgust and Surprise, respectively, after training of 20% of the MMI dataset.

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## 5 Conclusion and Future Work

This work presented a weightless neural network approach to the classification of facial expressions of emotion, which proved to be efficient in terms of accuracy. As it was not possible to obtain available code of the related cited solutions found in the literature for an adequate comparison, it was not possible to provide a fair comparison in terms of speed of learning. In terms of accuracy, WiSARD has proven to be competitive with current state-of-the-art for emotion classification, although automatic face detection still needs to be improved. Exploring combinations of detection of AUs, EMFACS coding and micro-expressions in order to improve emotion classification and facial recognition, are immediate future work that can be cited.

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