

HUMAN COMPUTER INTERACTION- APPLYING FUZZY C-MEANS, RECURRENT NEURAL NETWORK AND WAVELET TRANSFORMS FOR VOLUNTARY EYE BLINK DETECTION

Arezou Akbarian Azar^{1,2}, Alireza Akhbardeh^{1,2}

¹Institute of Signal Processing, Tampere University of Technology, Tampere, 33101, Finland,

²School of Biomedical Engineering, Science, and Health Systems, Drexel University, Philadelphia, PA 19104, USA, Phone: +1 (215) 895-2215;

Emails: akbarian@cs.tut.fi (arezou@drexel.edu), akhbarde@cs.tut.fi (alireza@drexel.edu)

ABSTRACT

Eye blink Classification & latency computation is one of the interesting areas of the man-Machine interaction. However, overlapped eye blinks, whilst doing fast blinking, increase complexity of the system. In this paper, we developed a Neuro-Fuzzy system using Shift-Invariant Wavelet transforms to overcome this problem. It has been shown that our suggested procedure has high-resolution and is able to classify eye blinks and compute their latencies.

1. INTRODUCTION

Eye blinks and eye movements provide “Window” through which we can understand many aspects of thought as well as language usage. Eye blink is achieved through the contraction of sets of muscles of eye and produces an electricity signal called Electro-Myogram which is a “pulse envelope or Spike” that may last for a fraction of a second. Orchard & stern in 1991 identified three types of eye blinks: (a) reflex blinks (in response to something invading in the eye), (b) Voluntary blinks (as a result of a decision to blink), and (c) endogenous blinks (due to perception and information processing). These eye blinks are the focus of interesting Psychological research. Reflex blinks are instinctive response that guards the eyes against air puffs and dust; they are also part of the startle response to loud noises. The blink reflex can be classically conditioned to a neutral stimulus such as a tone. After several pairings of a tone and air puff, the tone itself will generate the blink. This has been shown in class demonstrations. Voluntary blinks include squinting and winking; they are under conscious control. Applications of voluntary blinking include their use as control signals for communicating when diseases (such as AIDS, Multiple Sclerosis, Muscular Dystrophy, or Alzheimer’s) have made other forms of communication impossible. Endogenous (meaning “originating from or due to internal causes”) blinks occur during reading or speaking and reflect changes of attention and changes in thought processes. The

more attention required by a task, the fewer endogenous blinks occur. The typical duration of eye closure during blinks is 40 to 200 milliseconds. Useful and important information for distinguishing among the various forms of eye blinks is provided by the fact that their pulse envelopes (spikes) reliably differ in both duration and amplitude. The pulse envelopes are the outer border of the pulse [1]. An interesting issue to investigate is at which instant and which kind of blinks occur. Voluntary blinks can be used as control signals to send commands to machine to control it (Man-Machine interaction aids). On the other hand, it is possible to generate different commands using voluntary eye blinks with different instants of occurring (latency) or durations. To record Eye movements and Eye blinks, four electrodes (sensor) can be used as shown in Fig 1 [2]. Example of such eye blinks is shown in fig. 2 [2]. As can be seen, Eye blink occur in vertical channel of recording with different styles of pulse envelope (spike) and duration according to the kind of Eye blinks.

Because Eye blink has pulse envelope (spike) style, we must use spike discrimination methods to develop our method in eye blinks classification and latency computing. During the past several years, a large number of spike style signals-discrimination methods have been developed, including single and multi channel template matching, principle Component analysis, amplitude separation, Fourier analysis, linear filtering autoregressive modeling, neural

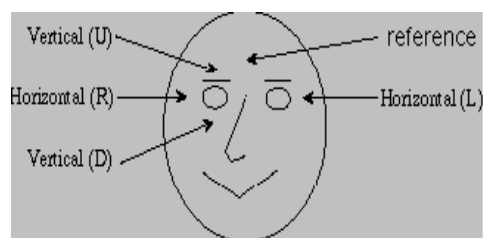


Fig. 1. Bipolar electrodes placement to record Eye movements. To detect value of horizontal movement, it must be computed difference value of two horizontal movement signals. For vertical movement, it shall be done the same methods [2].

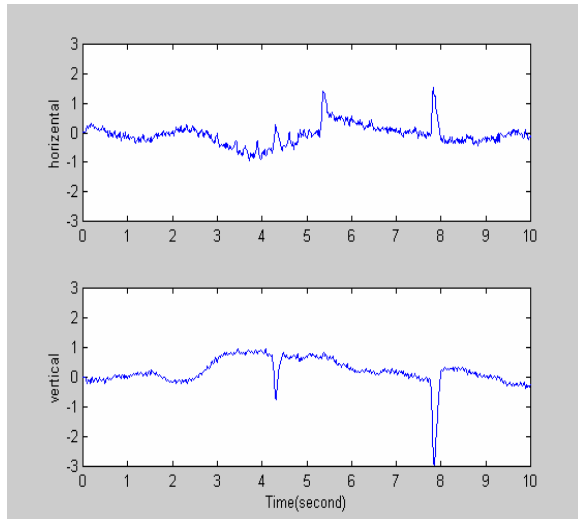


Fig. 2. Recorded Eye movements: As can be seen, Eye blink occur in vertical channel of recording with different styles of pulse envelope (spike) and duration according to kind of Eye blinks [2].

networks, and maximum likelihood approaches. Some of these methods have been reviewed by Schmidt [4, 5]. Most of the existing methods perform very well when the problem of overlapping spikes is not considered. However, methods that do not deal with such an important issue potentially may ignore importance information. Other limitations of the existing techniques concern their degree of success in the case of multiple templates, their ease of hardware and/or software implementation, their portability across platforms, and their suitability for real-time processing.

We proposed a new method for eye blink extraction and classification using fuzzy clustering, and dynamic artificial neural network. To compute eye blink latency, shift-invariant Wavelet transform was used. Our suggested procedure includes three stages: 1- Learning stage to determine the number of Eye blink classes and find a template signal as a candidate for each class; 2- Classification stage to clarify every eye blink based on obtained templates; 3- The latency computation using shift-invariant Wavelet transform. The learning stage uses a small part of signal and the Nearest Neighborhood Fuzzy clustering to extract templates (number of templates is the same as number of classes) [6]. Fuzzy C-means and dynamic artificial neural network were used to classify Eye blinks.

2. PROCEDURES

2.1 Templates extraction using the Nearest Neighborhood Fuzzy clustering system

This method is one of the effective and simple methods to classify data. The method is based on

selecting the first data as the center of first cluster. If distance of next data is less than neighborhood radius- an initial value, this data will belong to this cluster, else this data will be center of the new established cluster. This routine must be repeated for other input data to determine final clusters. To extract templates for eye blinks, maximum, minimum and mean of Eye blinks of a small segment of entire signal must be computed. These features are presented to the Nearest Neighborhood Fuzzy clustering system. The number of generated clusters is the same as the number of eye blink classes in the signal, and center of each cluster represents features of template of related eye blink class.

2.2 Eye blinks classification using the Dynamic Artificial Neural Networks & Fuzzy C-means

2.2.1 Eye blinks classification based on Fuzzy C-Means [6]

Suppose $X = \{X_1, X_2, X_3, \dots, X_n\}$ is limited set of data in feature space R^p and C is integer number between 2, and n ($2 \leq C \leq n$). If $P(X)$ is complete set that includes all of X sets, the fuzzy C partition is $\{A_i \in P(X); 1 \leq i \leq c\}$, where $\bigcup_{i=1}^c A_i = X$ & $A_i \cap A_j = \emptyset$. The fuzzy C partition can be described by membership degree of x_k in subset $A_i (u_{ik})$. The fuzzy C partition space for set X is:

$$M_{fc} = \{u \in \mathbf{n}_{cn} \mid u_{ik} \in [0,1], 1 \leq i \leq C, 1 \leq k \leq n, \sum_{i=1}^c u_{ik} = 1\}$$

It has been proved that U^* an optimal partition causes to optimize $J_m: (M_{fc} \times R^{cp}) \rightarrow R$, where J_m is:

$$J_m(U, V) = \sum_{k=1}^n \sum_{i=1}^c (u_{ik})^m \|x_k - u_i\|^2, 1 \leq m \leq \infty,$$

where that $d_{ik}^* = \|x_k - \mathbf{n}_i^*\|^2 > 0 \forall i, k$. If (U^*, V^*) is local optimal value for $J_m (m > 1)$, C means theory say:

$$\mathbf{n}_i^* = \frac{\sum_{k=1}^n (u_{ik}^*)^m x_k}{\sum_{k=1}^n (u_{ik}^*)^m}; 1 \leq i \leq c \quad (1-a)$$

$$u_{ik}^* = \frac{1}{\sum_{k=1}^n \left(\frac{d_{ik}^*}{d_{jk}^*}\right)^{1/(m-1)}}; 1 \leq i \leq c, 1 \leq k \leq n \quad (1-b)$$

Suggested approach to classify Eye blinks using

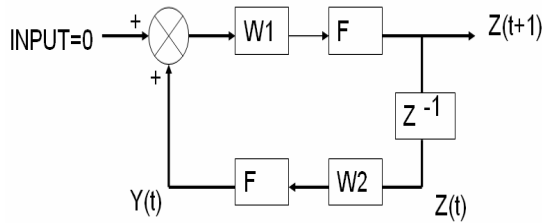


Fig. 3. A Multi-layer dynamic (recurrent) Network.

this clustering method is as following:

1- If $T=\{t_1,t_2,\dots,t_m\}$ are templates set, consider new template (t_{m+1}) that is mean of T set.

2- Set $C= m+1$ for fuzzy c-means and present $X=\{sp,t_1,t_2,t_3,\dots,t_{m+1}\}$ to fuzzy c-means classifier, where sp is Eye blink that should be classified.

Note: If sp and t_{m+1} belong to the same cluster, it means sp does not belong to classes 1 to m .

2.2.2 Eye blinks classification using dynamic neural networks

As we know, Hopfield Network is a dynamic network with feedback from input to output. If dynamic property of Hopfield is used in a multi-layer network, we can obtain a dynamic multi-layer network as shown in Fig. 3. We used this kind of networks and Hopfield neural network to classify eye blinks.

2.2.2.1 Dynamic neural networks for eye blink classification

First, templates must be stored on network, but these templates are time series and it is hard to store them. Therefore, we suggest obtaining sum of binary code of each template and their shifts to generate a unique code as following:

$$\begin{array}{cccccc}
 & x & x & \dots & x & x \\
 x & . & . & \dots & x & \\
 . & . & . & . & & + \\
 & & & & & . \\
 x & . & . & x & x & \\
 \hline
 x & x & . & . & . & x & x
 \end{array}$$

We repeated this routine for All of Eye blinks data. Then, these codes must be mapped from region $\{0,1\}$ to $\{+1,-1\}$ for Hopfield and $\{-0.9,+0.9\}$ region for dynamic multi-layer network. These codes are presented to networks to store in weights. According to the Hamming distance, Eye blinks codes attract to one of stable points, so the eye blink belongs to the cluster with fix point that is template codes of an Eye blink class (Number of classes is between 1 and m).

Note: if number of fix points is more than “code length multiply to 0.15”, pseudo fix points disturb performance of network [8].

2.3 Eye blink latency computation based on shift-invariant Wavelet transforms

2.3.1 Wavelets as a time-frequency analyzing method

The continuous wavelet transform of a square-integrable function $f(t)$ is defined as

$$wf(s,t) = \int_{-\infty}^{+\infty} f(\mathbf{t}) \frac{1}{\sqrt{s}} \mathbf{y}\left(\frac{t-\mathbf{t}}{s}\right) dt$$

and t are the scale (or frequency) and time variables, respectively. The function $\mathbf{y}(t)$, called a wavelet, must satisfy the admissibility condition, i.e. it must be a zero-mean, square-integrable function. In practical applications the parameters s and t must be quantized. The simplest method is dyadic kind. By using it, the fast Wavelet transform can be presented as follows:

$$wf[n,2^j] = \sum_{m=0}^{N-1} f[m] \mathbf{y}_j[m-n] = f[n] * \mathbf{y}_j[n]$$

Where $\mathbf{y}_j[n] = \mathbf{y}\left(\frac{n}{2^j}\right)$ and $f[n]$ is sequence with length of N , and the sign $*$ presents circular convolution. If wavelet transforms of $f(t)$ and $f(t - \mathbf{t})$ are the same, this kind of transform called Shift-invariant. One of these kinds of wavelets is dyadic wavelet explained below.

2.3.2 Dyadic Wavelets [9,10]

This is a transform with scale parameter quantized around a dyadic sequence $\{2^j\}_{j \in \mathbb{Z}}$. To decline information redundancy, we can use maxima wavelet that use only locally maxima values of wavelet coefficients and ignore other values, i.e. if local maxima is located at: $u_{j,p}$

$$\tilde{d}_j[m] = \begin{cases} d_j(m) & m = u_{j,p} \\ 0 & \text{[9]} \end{cases}$$

produced wavelet representation will have a few information redundancies. Also it is suggested to present wavelets using amplitude and phase of Wf . Magnitude vector $M(wf)$ is obtained by simply sorting the values of the vector $\{wf_{2^j}\}_{j \in (1,J)}$ in increasing order. The phase vector $P(wf)$ is obtained by indicating position that each component of the magnitude vector had in original wf prior to sorting. Magnitude vector $M(wf)$ and

$M(wf(t - \mathbf{t}))$ are the same, because dyadic wavelet transform is shift-invariant, but it's not true for phase vectors.

2.3.2 Latency computing algorithm

Assume that an original signal (template) $x[n]$ is known, so the vectors $M(WTx)$ and $P(WTx)$ are available. Through the following steps, we can compute latency of signal:

1. Compute WTx_{n_0} .
2. Construct the magnitude and phase pair, $M(WTx_{n_0}), P(WTx_{n_0})$, respectively.
3. Replace the phase vector $P(WTx_{n_0})$ with $P(WTx)$.
4. Compute the inverse transform of the resulting magnitude-phase pair $\{M(WTx_{n_0}), p(WTx)\}$ to obtain a reconstructed $x^*[n]$.
5. the exact amount n_0 of time shift between $x[n]$ and $x_{n_0}[n] = x[n - n_0]$ is given by the following expression;

$$\left| \max_t P(WTx) - \max_t P(WTx_{n_0}) \right|$$

In eye blink latency computation, $\{x[n]\}$ are templates without any time shift and $\{x_{n_0}[n] = x[n - n_0]\}$ are eye blinks that we want to calculate their latency. This method is not sensitive to noise of signal [3] and gives us the exact amount of spike latency (Fig. 4).

3. SIMULATIONS AND RESULTS

Because Eye blink has pulse envelope (spike) style (see Fig 2), we should be familiar with spike discrimination methods and develop our method to implement eye blink classification and latency computation. To demonstrate performance of these approaches and to compare their results, we need to generate a spike style waveforms train. To generate this kind of train, we used three templates (t_i) with different styles and different durations, shown in Fig. 5 (a). These templates have been shifted randomly with Gaussian distribution ($t_i(n + n_i)$) and multiplied to a random number with uniform distribution, ($A_i, i = 1,2,3$), and added to a random sequence with Gaussian distribution as a background noise (Bck_noise):

$$Sp - train = \sum_{i=1}^3 A_i * t_i(n + n_i) + Bck_noise$$

After twenty repetition of this process, generated sequences have been added to each other to produce final artificial spike train (Fig. 5 (b)). First, a small segment of this train (200 samples) has been presented to the Nearest Neighborhood Fuzzy clustering stage. As we expect, this classifier extracts 3 templates and recognizes 3 classes correctly. Then, rest of the data was presented to several classifiers including Fuzzy C-means, Hopfield, dynamic one-layer and dynamic two-layer neural networks. Table (1) shows classification performance of these approaches. As shown in table (1), Fuzzy C-means method has better performance and faster than others. Dynamic multi-layer neural network is in second place compared to fuzzy c-means, while Hopfield doesn't have good performance because of pseudo points that disturb operation of Hopfield. According to the fig. 6 (b), some spikes have overlap with each other, but applied approaches in this paper, as shown in table (1), were able to discriminate overlapped blinks. To compute latencies of spikes (n_i), shift-invariant wavelet transforms was used.

4. CONCLUSION

To discriminate spike style eye blinks, in this paper, we proposed approaches which have high performance, even with overlapped eye blinks. In our approach to overcome overlapping phenomena, the

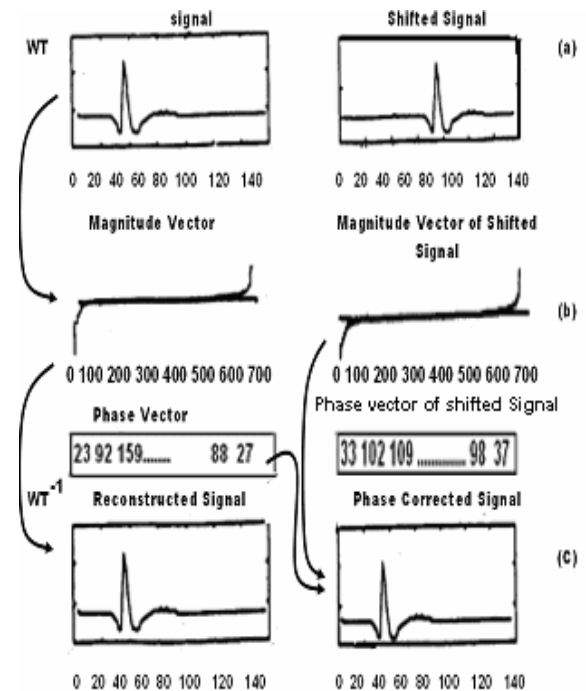


Fig. 4. Examples of latency correction of transient signals using the shift-invariant wavelet transforms.

first step is to answer this question: which kinds of Eye blinks and how many classes appeared in the signal? To discriminate eye blinks and classify them, we need to find a template (representative) for each eye blink class.

Eye blink spike classification is very important to find type of user command. The first stage of our man-machine interaction system is the Nearest Neighborhood Fuzzy clustering to classify eye blink spikes to find templates (representatives) for each class using a small segment of data. Four different Classifiers were used to classify eye blinks using

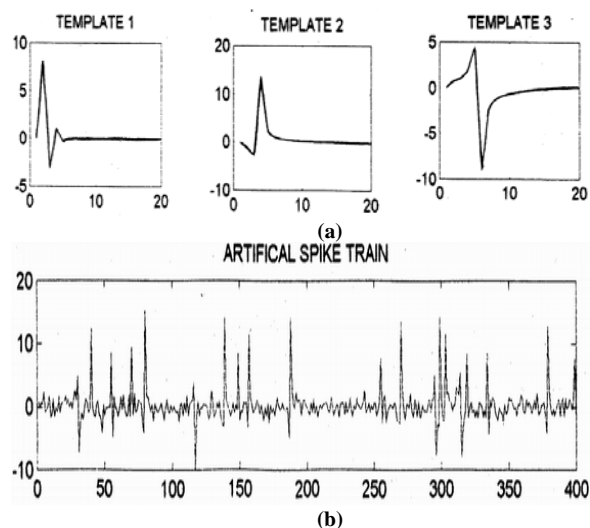


Fig. 5. (a). An Example of Templates used by spike train. (b). Example of a spike train generated to test performance of Classifiers and latency computing.

TABLE 1
RESULTS OF SPIKES CLASSIFICATION USING NEURO-FUZZY APPROACHES AND SPIKE TRAIN SHOWN IN FIG. 5. SHIFT-INVARIANT WAVELET TRANSFORMS ARE USED FOR COMPUTING SPIKES LATENCY

S.N.	C.Cl	F.C.M	HP.N	F.ILP	F.2LP	S.Lt
1	3	3	3	3	3	31
2	2	2	2	2	2	40
3	1	1	1	1	1	55
4	1	1	1	1	1	70
5	2	2	UND	2	2	80
6	3	3	3	3	3	117
7	2	2	2	2	2	139
8	1	1	1	1	1	149
9	2	2	2	2	2	157
10	2	2	2	2	2	188
11	1	1	1	1	1	255
12	2	2	2	2	2	270
13	3	3	3	3	3	296
14	2	2	2	2	2	299
15	2	2	2	2	2	303
16	3	3	3	3	3	314
17	1	UND	UND	UND	UND	319
18	1	1	1	1	1	334
19	2	2	2	2	2	379
20	1	1	1	1	1	399

S.N=Spike Number, C.Cl=Correct Class, F.C.M= FUZZY C-MEANS, HP.N = Hopfield Network, F.ILP= one layer dynamic net (Improved Hopfield), F.MLP= Feed forward Multi-layer Network, S.Lt= Spike Latency (in ms), UND= undefined class.

obtained templates. By comparing these classifiers, Fuzzy C-means and the dynamic multi-layer neural network had higher performance than other methods. To calculate eye blink latencies, shift-invariant Wavelet was used which gave very good estimation of eye blink latencies. As an extra ability, our approach is not limited to only Eye blink data and can be used in other field of biomedical signal processing such as EEG spikes during epileptic seizures, neurons activities, and evoked potentials.

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