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CONTENTS

THE COGNITIVE MODELS USING OSCILLATORY NEURAL NETS

M. Atasoyu and S. Ozoguz

***Abstract*—** Oscillatory neural nets needs energy efficient neurons and synapses in its hardware implementation, as a candidate, Magnetic Tunnel Junctions (MTJ), which are known energy efficient devices [1-3], can be functioning as a neuron or synapse in a neural net**.** In this work, we have proposed a Phase Locked Loop (PLL) based Oscillatory Neural Network (ONN) for binary image recognition. The ONN architecture is proposed and possible design aspects are presented. The response time of the network may be faster with respect to the operating frequencies of the STO.

***Keywords*—** *Cognitive, Neuron, PLL, MTJ*

1. INTRODUCTION

THE era of quantum-inspired devices and cognitive brain-based computing, such as pattern recognition applications, has become an interesting area of research. In such a calculation, the basic structure consists of neural networks that mimic the cognitive functions of the brain. These networks are composed of neurons and synapses, known to be energy efficient devices in their hardware implementation, such as MTJ, known to be efficient energy devices [1-3], as well as a neuron. or synapse in a neural network. Many different architectures have been proposed as a neural network [1-6]. However, physically, the phase relationship between neurons and synapses [6] was attracted by a network of neurons, oscillating neural network (ONN), exploiting the synchronous oscillatory behavior of neurons for image segmentation [1.6]. The ONNs were developed [1] and [4-9] in these designs, a neuron modeled as a locked phase (PLL).

In this work, we have proposed a new architecture based on MTJ devices as an oscillator that is a spin torque oscillator (STO) and whose increased phase stability of the PLL using frequency dividers differs from [1].

2. OSCILLATORY NEURAL NETS

STOs is composed of a perpendicular free layer, an in-plane pinned layer, and a barrier layer, as shown in Fig.1. The maximum power of the STO is reported in [10], and we modeled STO in Verilog-AMS by modifying given a model in [12], while capturing the dynamic behavior of an STO via the LLGS equations [11], and the parameters of the STO are taken from [10]. STO is a microwave signal source in a proposed PLL structure. The oscillation gain for different biasing currents is given in Fig.2.

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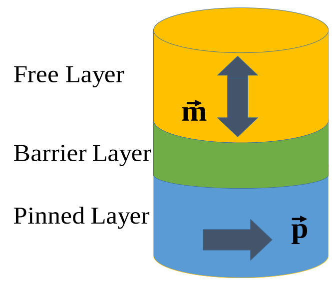

Fig.1. The physical layer structure of STO.

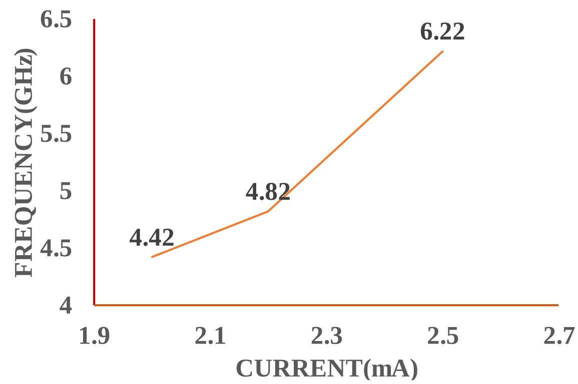

Fig.2. The gain of STO with different biasing currents.

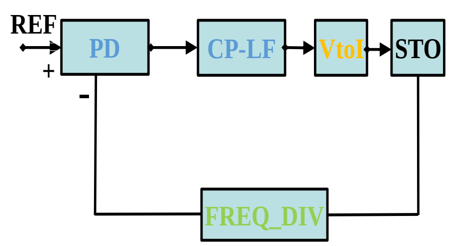

Fig.4. The proposed PLL is as a neuron.

In the proposed PLL, the design comprises a phase-frequency detector, a loop filter, a voltage-current converter and the STO, illustrated in Fig.4. The structure of the neural net proposed in [4,6], illustrated in Fig.5. The main concern is that the image recognition is associated with the synchronization of the neurons [6].

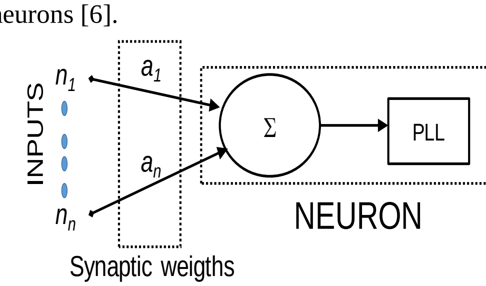

Fig.5. The proposed PLL is as a neuron [4].

3. COGNITIVE PERCEPTION

The ONN architecture project was first proposed by Izhikevich in [4] and the first use of STOs in [1]. The complexity lies in the architecture because each neuron is represented by a single PLL, as shown in Fig.5. To train the synaptic weights of the ONN are applied by a Hebbian learning rule [4]. To test the proposed network, a possible test architecture structure is in Fig.6 and also the possible test images are given in Fig.7a and in Fig.7b, and in the training and identification setup 10x6 three binary images, proposed in [1,5], can also be used.

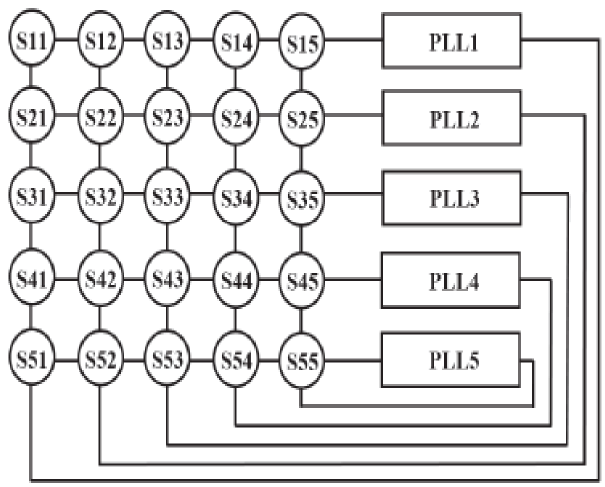

Fig.6. The ONN architecture [1].

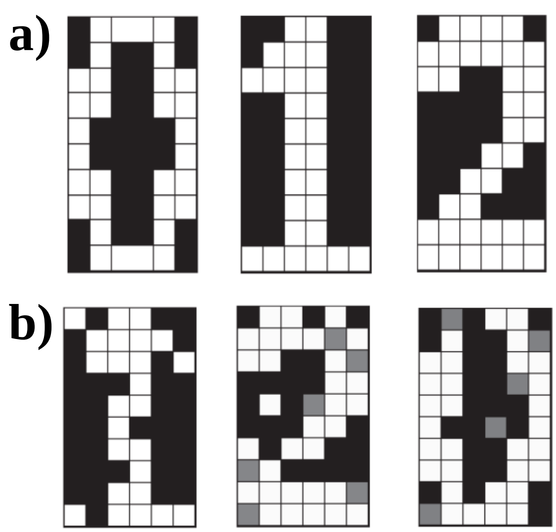

Fig.7. a) Training data and b) distorted image for the recognition [1].

4. CONCLUSIONS

In this work, we have proposed a PLL based ONN for binary image recognition. The ONN architecture is proposed and possible design aspects are presented. The response time of the network may be faster with respect to the operating frequencies of the STO.

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BIOGRAPHIES

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HIGH PERFORMANCE DECODING OF BEHAVIORAL INFORMATION FROM MEAN BACKGROUND ACTIVITY IN EXTRACELLULAR NEURAL RECORDINGS

M. Okatan, and M. Kocatürk

Abstract— We have previously shown that the standard deviation of background activity in bandpass filtered extracellular neural recording snippets is strongly modulated by behavior such that it can be used to decode behavioral variables with up to 100% accuracy. Here we show that the mean background activity is also strongly modulated by behavior and that it too can be used to decode behavioral variables with up to 100% accuracy. To the best of our knowledge, our method extracts the weakest signal that has ever been extracted from extracellular neural recordings, which can still be used to decode a behavioral variable with very high accuracy. Our results demonstrate that both the standard deviation and the mean of the background activity can be exploited in brain-machine interfaces.

Keywords— *Computational Neuroscience, Truncation Thresholds, Amplitude Thresholding, Brain-Computer Interfaces*

1. INTRODUCTION

Extracellular neural recordings provide a wealth of information about the information encoded in the spiking activity of individual and populations of neurons [1]. In the past several decades this technique has yielded substantial amounts of information about what types of movement-related information are encoded in the activity of individual neurons in the motor cortices [2]. At the turn of this century brain-machine interface systems that use such information to infer behavioral variables have become a reality [3]. Initially, such systems decoded behavioral variables by modeling the spiking activity of populations of neurons. However this approach requires first to recover the spike trains of individual neurons from extracellular neural recordings; a process called spike sorting. In spike sorting extracellular recordings are first bandpass filtered with a pass band that is suitable for spike detection. Bandpass filtered recording is then thresholded and suprathreshold waveforms are clustered in high-dimensional feature spaces to identify the spikes fired by distinct neurons [4]. Usually a high threshold, such as three to five times the standard deviation of the filtered recording (3-5σ), is used as the threshold to make sure that suprathreshold waveforms are sufficiently well-defined and can from distinct clusters [5, 6, 7]. As the number of electrodes increased in advanced brain-machine interface systems, spike sorting emerged as a computational bottleneck for real-time decoding of behavioral information from extracellular neural recordings. This led researchers to question whether decoding could be carried out without spike sorting [7]. It was found that decoding could indeed be performed without spike sorting but that thresholds in the range of 3-5σ were too high for that purpose [7]. This raised the problem of optimizing the threshold. It has been proposed that the threshold that maximizes the signal to noise ratio of the behavioral variable of interest in suprathreshold activity can be used as the amplitude threshold (SNR-threshold) [8]. While this method is more principled and usually yields thresholds smaller than 3-5σ, it does however depend on the behavioral variable of interest. Therefore more information may be available in the filtered recording than what the SNR-thresholds yield. Exploring the nature of that residual information would be informative from the point of view of both basic neuroscience research and brain-machine interface technology. This issue of residual information has been addressed by a method that we developed to automatically compute a pair of amplitude thresholds for filtered recordings using only neural data in a fully data-driven way [9]. Our method computes a pair of thresholds, called *truncation thresholds*, such that the distribution of the subthreshold data obeys a well-defined noise distribution according to Kolmogorov-Smirnov test with a significance level greater than 0.05 and the thresholds are as far away from each other as possible. This method yields thresholds far below 3-5σ in real data [9], attesting to the fact that there is more information in filtered recordings than what is extracted using 3-5σ thresholds.

The mean (μ_{tr}) and the standard deviation (σ_{tr}) of the background activity are automatically estimated by maximum likelihood in our method as a byproduct of the computation of the truncation thresholds. We have previously shown using simulated data that σ_{tr} is more accurate than alternative scale estimators, such as the conventional standard deviation formula, robust median estimator, mean absolute deviation, S_n, Q_n, trimmed estimator, winsorized estimator and DATE [9, 10, 11]. Moreover, we have shown that, in extracellular recordings from the rat primary motor cortex, σ_{tr} exhibits significant changes in different periods of a behavioral task where subjects press a right or left lever with their respective front paw in response to a visual stimulus [12]. This modulation is so strong that what lever the subject presses can be inferred with up to 100% accuracy using a logistic regression model where the independent variables are σ_{tr} estimates obtained from filtered recording snippets in the vicinity of the lever pressing time. These results showed for the first time in the literature that samples that would normally be considered

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noise in filtered extracellular neural recordings are actually very informative about the subjects' behavior.

The present study continues along the same lines and explores whether μ_{tr} too depends on behavior and whether it too can be used to decode behavioral variables with high accuracy.

2. METHODS

In this section first the data that are used in the analyses are explained. Next, the estimation of μ_{tr} is presented. Finally, the logistic regression modeling of the lever pressing behavior is explained. All computations were performed in MATLAB (R2015a, MathWorks, Inc., USA) under 64 bit Windows 8.1 Single Language (2013) operating system on a laptop computer with 6 GB RAM and 2.60 GHz Intel® Core™ i5-3230M CPU.

2.1. Data

Neural and behavioral data were recorded from a rat by one of the authors (M.K.) in a previous study. The recording was made using a neuroprosthetic design environment [13] from the primary motor cortex (area M1) of a rat during lever-pressing in response to visual stimuli. In the experimental setup the rat initiates a trial by a nose poke into a port equipped with a photodetector. This triggers a visual stimulus that informs the subject about whether pressing the right or the left lever is the correct response at that trial. The subject responds by pressing the right or the left lever using its ipsilateral front paw. Correct responses are rewarded by approximately a 0.03 ml water reward. The experiment consists of 82 trials. The subject failed to respond at one trial and gave an incorrect response at another trial. The present analysis uses the data obtained in the remaining 80 trials. Neural data were recorded using a 16-channel microelectrode array with a sampling rate of 40 kHz per channel. Eight microelectrodes were implanted in each cortical hemisphere. Data were then digitally bandpass filtered between 400 Hz and 8 kHz using a 4th order Butterworth filter. The responses of the subject were recorded as a binary series in which a 0 represents a left lever-press and a 1 represents a right lever-press.

The length of the time interval between the start of the recording and the initiation of the trial, as well as the response time of the subject, are different at each trial. At each trial there is at least a 2 s recording time before the trial is started by the subject, and at least 0.8 s between the start of the trial and the time of response. At each trial neural recording continues for at least 1 s after the response is given.

To examine the dependency between neural activity and behavior, truncation thresholds, along with σ_{tr} and μ_{tr}, have been computed at each trial for eight recording snippets of 0.5 s duration each (Fig. 1 and Fig. 2). These snippets correspond to the 2 s interval immediately preceding the start of the trial (pre-start; PRS for short), the 0.5 s interval immediately following the start of the trial (post-start; POS for short), the 0.5 s interval immediately preceding the response (pre-response; PRR for short) and the 1 s interval immediately following the response (post-response; POR for short). In this way, the PRS epoch consists of four consecutive snippets, the POS and PRR epochs consist of one snippet each, and the POR epoch consists of two consecutive snippets (Fig. 2).

2.2. Estimation of μ_{tr}

μ_{tr} is estimated automatically as a byproduct of the computation of truncation thresholds. The source code and standalone executables of the software that computes the truncation thresholds are registered with SciCrunch.org under the name "Truncation Thresholds Software" (RRID:SCR_014637) and are freely available. The algorithm implemented in this software has been explained in detail in our previous work [9, 14]. Briefly, the algorithm uses the bisection method [15] to iteratively compute the truncation thresholds in three steps. The cardinality of the set of candidate solutions is halved at each iteration. For a time series consisting of N samples the algorithm reaches the solution in approximately $log_2(N^3/4)$ iterations. The algorithm generates approximately $log_2(N)$ pairs of candidate thresholds and picks the pair that yields the widest interval and for which the distribution of the subthreshold samples is statistically indistinguishable, according to Kolmogorov-Smirnov test at level $P \geq 0.05$, from a truncated normal distribution, truncated at the threshold values. The standard deviation (σ_{tr}) and the mean (μ_{tr}) of the truncated normal distribution are estimated by maximum likelihood from the data.

In the present analysis μ_{tr} is estimated using the Truncation Thresholds Software (version in English dated 25.01.2018) for each 0.5 s snippet described in Section 2.1. For each of the 16 channels, whether μ_{tr} estimates obtained in the left and right trials differ from each other is tested using the Kruskal-Wallis test separately in the first four (PRS epochs) and the last four (POS, PRR and POR epochs) of the eight epochs considered here.

2.3 Modelling of the response type as a function of μ_{tr}

Response type (0: left; 1 right) has been modelled as a function of the μ_{tr} estimates obtained from the POS, PRR and POR epochs using quadrivariate logistic regression. The parameters of the model have been estimated by maximum likelihood using the glmfit.m function of MATLAB (MathWorks, Inc., ABD) under a binomial probability model for the response type. The output $o[d]$ of the model at trial number d is calculated using the glmval.m function with a logit link function; $1 \leq d \leq \mathrm{D}$, where D is the total number of trials considered, which is 80. If $o[d] > \theta$, then the model is accepted to predict that the right lever was pressed at that trial; otherwise the model is accepted to predict that the left lever was pressed at that trial. The decision threshold θ was determined separately for each electrode by dividing the interval $\left[\min_d o[d], \max_d o[d]\right]$ into 99 equal pieces, yielding 100 candidates for θ, and selecting the smallest candidate that maximized the accuracy, where the latter is defined as the total number of true positive and true negative predictions divided by D [16].

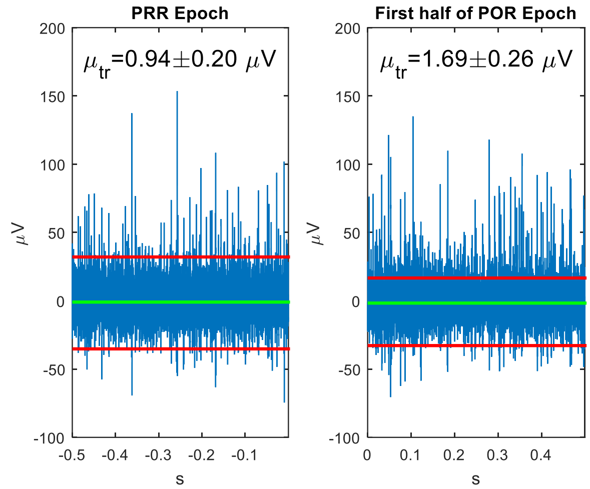

Fig.1. Recording snippets, truncation thresholds (red) and μ_{tr} estimates.

3. RESULTS

Figure 1 shows the filtered recording snippets corresponding to the PRR and the first half of POR epochs at trial 30 collected from electrode 4 (counting from zero) implanted in the left hemisphere, along with the estimated μ_{tr} values and their 95% confidence intervals. Truncation thresholds are shown in red, while μ_{tr} estimates are shown in green. The subject pressed the left lever at this trial and the response time corresponds to 0 s in Fig. 1.

Figure 2 shows μ_{tr} estimates from the same electrode at all trials in different behavioral epochs. The top four graphs show estimates obtained from the last two seconds before the trial is started (PRS). In the bottom row, the leftmost graph shows estimates obtained from the first 0.5 seconds after the trial is started (POS), the next graph shows estimates obtained from the last 0.5 seconds before the response is given (PRR), the last two graphs show estimates obtained from the first 1 second after the response is given (POR).

The difference between the μ_{tr} estimates obtained from the left versus right trials in the PRS epochs was not statistically significant in any of the electrodes ($P\geq0.05$). By contrast the difference between the μ_{tr} estimates obtained from the left versus right trials in the POS, PRR and POR epochs was statistically significant in eight electrodes ($P<0.05$).

TABLE I
PREDICTION ACCURACY

	Electrode	Accuracy (%)	θ
Min.	8, 9	74	0.60, 0.52
Max.	3, 4, 6	100	0.01
Mean ± s.e.m	-	87.7±2.5	0.37±0.06

The results of the regression analysis that modelled the response type as a function of the μ_{tr} estimates obtained from the POS, PRR and POR epochs are summarized in Table 1. The lowest accuracy was obtained as %74 at electrodes 8 and 9 (both in the right hemisphere). High values of the decision threshold (0.52 and 0.60) indicate that the model failed to generate a low probability for a "right response" at left trials in these electrodes. By contrast data from electrodes 3, 4 and 6 (all in the left hemisphere) predicted the response type with 100% accuracy. It is seen that the decision threshold is as low as 0.01 in these electrodes. Namely the output of the regression model is so close to 0 on the left trials that the first non-zero decision threshold candidate succeeds in predicting the response with 100% accuracy. The average accuracy across all 16 electrodes was about 88%. There was no hemispheric difference in prediction accuracy ($P\geq0.17$;

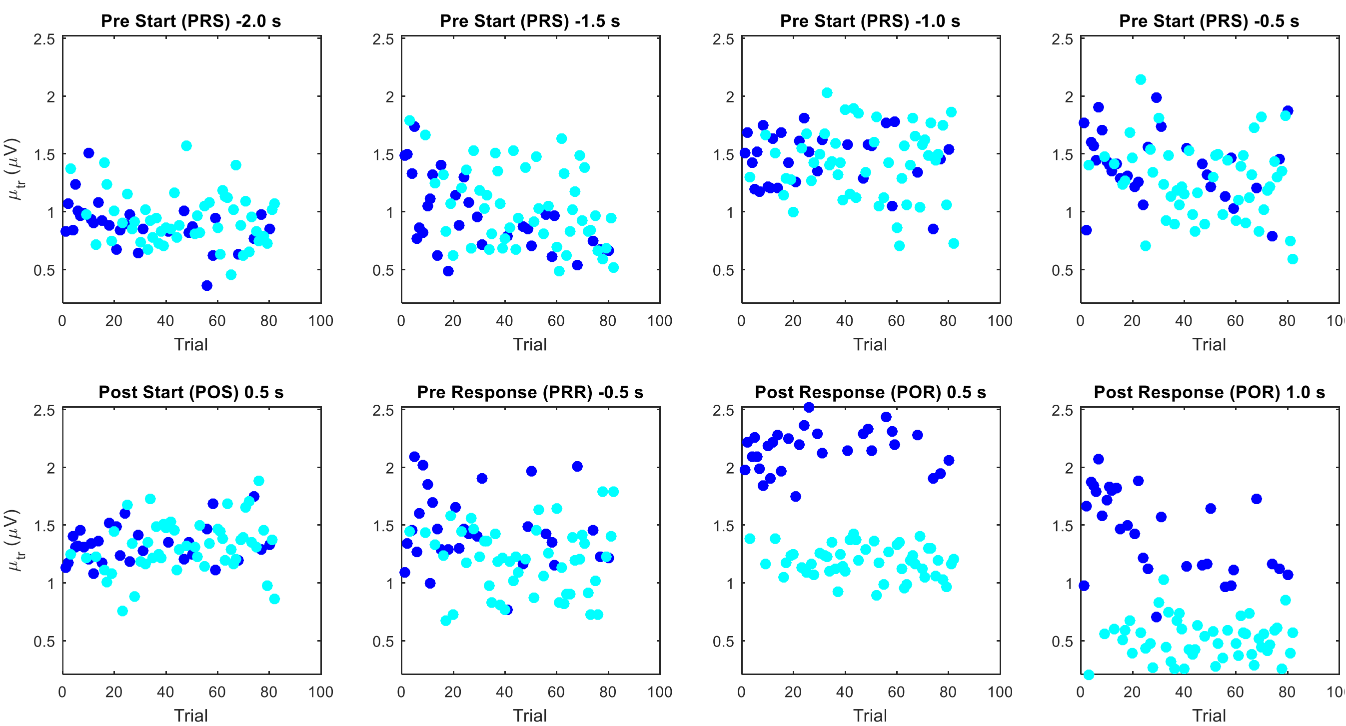

Fig.2. Change in μ_{tr} with behavior. Estimates from left (right) trials are shown in dark (light) blue.

Kruskal-Wallis test).

4. DISCUSSION

Information is usually extracted from extracellular neural recordings by thresholding the amplitude of the filtered recording and using the suprathreshold data. We have previously shown, for the first time in the literature, that the standard deviation of the subthreshold data (σ_{tr}) can also be used to extract behavioral information from these recordings with very high accuracy [12]. The present results show that the mean of the subthreshold data (μ_{tr}) too can be used for this purpose with a similar performance.

Figure 1 and Fig. 2 show that behavioral modulation of μ_{tr} is a very weak but consistent signal. The average difference between the μ_{tr} estimates obtained in the left versus right trials in the first half of the POR epoch is about 1 μV (Fig. 2). In Fig.1, the μ_{tr} estimates obtained from consecutive 0.5 s intervals intercalating the response time differ by only 0.75 μV, yet this difference is significant as indicated by the non-overlapping 95% confidence intervals of these estimates. To the best of our knowledge, these results suggest that our method extracts the faintest signal that has so far been extracted from extracellular neural recordings while still being capable of inferring behavioral variables with up to 100% accuracy.

The background activity, which forms the subthreshold data in these analyses, contains information about the ensemble spiking activity of a large number of neurons located far from the recording electrode. Therefore firing rate changes across relatively large cortical areas may result in changes in the statistical structure of the background activity. The present results show that the mean background activity waxes and wanes slightly but consistently as a function of behavior. In bandpass filtered recordings the overall mean is identically equal to zero, since the DC component of the signal has been filtered out. Yet the mean background activity may deviate from 0 when computed in short time windows, as it was done in the present analysis. By using time windows of 0.5 s duration time locked to behavioral events we have been able to show that mean background activity does indeed change with behavior and that this signal can be used to infer behavioral variables with very high accuracy.

The finding that μ_{tr} estimates obtained from time windows occurring before the start of the trial (PRS epoch) were not significantly different in the left versus right trials is not surprising since the subject does not yet have access to information about the correct response at that trial during that epoch. After the trial is started, however, a visual stimulus informs the subject about the correct response at that trial. Our results show that this information affects the mean background activity in some or all of the POS, PRR and POR epochs in some electrodes (Fig. 1, Fig. 2 and Table 1). This effect is so strong in some electrodes that when used in a logistic regression model to predict the response, the subject's response can be predicted with 100% accuracy (Table 1).

Truncation thresholds are a tool for segregating the signal and noise components of filtered extracellular neural recordings in a fully automated and data driven manner [9]. Naturally, more detailed information about the behavior is available in suprathreshold data. That is because suprathreshold data contain spikes fired by neurons located near the recording electrode, as shown in Fig. 1, and it is well known that different motor cortical neurons encode different aspects of the unfolding motor behavior [2]. Therefore it is necessary to use suprathreshold data to extract detailed information about behavior. However such analyses will involve additional computations. By contrast μ_{tr} is estimated automatically as a byproduct of the computation of the truncation thresholds. Our results show that our method can be used to decode coarse-grained behavioral information that is roughly encoded in the activity of large numbers of neurons, such as the right or left lever pressing in the present study, with very high accuracy and without recurring to suprathreshold data analysis.

5. CONCLUSIONS

Our results show that there is practically no *noise* in bandpass filtered extracellular neural recordings, in the sense that even the mean value of the background activity is significantly modulated by behavior. Provided that a clean recording has been obtained, virtually all samples that make up an extracellular neural recording are of neural origin and when taken in the aggregate, their statistics do carry information about the state of the organism. The results show that estimation of μ_{tr} using the truncation thresholds method is capable of detecting signal variations on the order of a microvolt in these recordings. The high sensitivity of our method is due to the computation of truncation thresholds, which are an original and novel tool for amplitude thresholding. Overall, these results suggest that the use of μ_{tr} can increase the performance of brain-machine interfaces when used in conjunction with existing decoding methods.

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PHYSICAL LIMITS FOR SELF-CONTAINED SYSTEMS: AN EXAMPLE OF THE HUMAN BRAIN AS A COGNITIVE SYSTEM

S. Seker and J. Dikun

***Abstract*—** This study presents the calculation of information rate using the Bremermann's limit for human-brain. In this manner, the information rate of the brain can be approximately calculated. This is the physical limit of the natural system as an example of the human-brain or a cognitive system.

***Keywords*—** *Self Contained Systems, Information Processing, Bremermann's limit, Brain and Launder's Limit*

1. INTRODUCTION

INFORMATION processing is executed by information processors or computer hardware's. Most important information processor is human brain. In life, the human brain system uses some mathematical models of the objects or things in the real life to recognize the reality and hence, it tries to get some matching between the models and objects. The Objects which carry meaning are represented by patterns called as symbols. As a result, to form the symbolic expressions, that constitute inputs to or outputs, from information processes, they are stored in the processor memory. And also, the memory stores the symbolic expressions. In an information processing system like the human-brain, the mathematical or abstract model is provided by the ability of its processing units.

Since 1980, the increasing attention has been focused on the study of the human brain as an information processor of the parallel type. This is related with the cognitive science and cognitive engineering which can be accepted as a further step of the Machine learning and Artificial Intelligence. From these different viewpoints, natural or artificial ones need to the processing or computing speed as a system capacity. For this reason, an upper limit of the computing speed is described and presented in this study [1,2].

2. BREMERMANN'S LIMIT FOR MAXIMUM COMPUTATION SPEED

Bremermann's limit for maximum computation speed is based upon the Shannon's channel capacity concept under the combination of quantum and relativity theories [3-8].The Shannon's formula that is related with the channel capacity. *C* for noisy channels is described as:

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$$C = BW.log_2(1 + \frac{S}{N}) \tag{1}$$

Where BW: Band width, $^S/_N$: Signal to Noise Power ratio. C is also channel capacity or maximum rate in bits per second [3]. Here, the band width is defined as maximum frequency in most cases and it becomes υ_{max}. In quantum physics, it is represented in the maximum energy formula as given by below:

$$E_{max} = h\upsilon_{max} \ . \tag{2}$$

Where h is Planck's constant.

Also another concept of the quantum physics is Heisenberg's uncertainty principle, where the uncertainty of the energy ΔE is measured in the time interval or uncertainty of time Δt depending on the following inequality.

$$\Delta E.\Delta t \geq h \tag{3}$$

Hence the equation (1), namely the Shannon's formula, can be written for $S = N$ and then it defines the maximum channel chapacity as below:

$$C_{max} = \upsilon_{max} log_2(1 + 1) = \upsilon_{max} \tag{4}$$

And using the Equations (2), the maximum channel capacity becomes

$$C_{max} = \upsilon_{max} = \frac{E_{max}}{h}. \tag{5}$$

Hence it means the maximum bit speed to be presented to the channel depending on the Shannon's opinion.

In quantum theory the continuouty of the energy interval of (0, E_{max}) can be represented by the interval of ΔE, hence, it is divided by *n* and defined as

$$\Delta E = \frac{E_{max}}{n} \tag{6}$$

Here it means that the same energy is distributed to *n*-channels if the first one of the Eq. (6) is substituted in the Equation (5), the channel capacity is written as follows:

$$C_{max} = \frac{n.\Delta E}{h} \ . \tag{7}$$

Also, using the Einstein's formula for the Energy,

$$E_{max} = mc^2, \tag{8}$$

where m is total mass and c is also speed of the light in vacumm. From this view point C_{max} is redefined for the equation (8) and it becomes

$$C_{max} = \frac{mc^2}{h}. \tag{9}$$

Getting the quality of the Equations (7) and (9), it is written as

$$\frac{n.\Delta E}{h} = \frac{mc^2}{h}. \tag{10}$$

In this equality, ΔE is changed, through the Equation (3), with the inequality of $\Delta E \geq \frac{h}{\Delta t}$

And, finally

$$\frac{n.(h/_{\Delta t})}{\Delta t} \leq \frac{mc^2}{h},$$

or it is

$$\frac{n}{\Delta t} \leq \frac{mc^2}{h}. \tag{11}$$

Here $(\frac{mc^2}{h})$ is in the unit of bit/sec depending on the left side of the inequality (11). Whereas c^2/h is in the unit of bit/sec/kg and it is known with the name of Hens-Joorchim Bremermann, so-called Bremermann's limit, as maximum computational speed of a self-contained system in the material universe.

Numerical value of the Bremermann's limit is $c^2/h = 1.36 \times 10^{50}\ bit/sec/kg$ where, $c = 3.10^8\ m/sec$, $h = 6.626.\times 10^{-34}\ m^2kg/sec.$

Also for each bit/sec, it is represented by the amount of heat energy equality of $(kT\ ln\, 2)$ ergs/sec or $10^{-7}(kT\ ln\, 2)$ with Watt/sec T: Temperature in Kelvin.

3. APPLICATION OF THE BREMERMANN'S LIMIT TO BRAIN AND LAUNDER'S LIMIT

Considering the brain mass (weight) as 1350 gr approximately in homogeneous structure, hence, using the inequality (Eq. 11) becomes

$$\frac{n}{\Delta t} \leq \frac{mc^2}{h} = m(\frac{c^2}{h}),$$

$$\frac{n}{\Delta t} \leq (1.35).(1.36) \times 10^{50}\frac{bit}{sec},$$

or,

$$\frac{n}{\Delta t} \leq 1.836 \times 10^{50}\ bit/sec\ . \tag{12}$$

Approximately, it becomes $2.10^{50}\ bits/sec$ and at room temperature $T = 273 + 20 = 293 \approx 300°K$ the maximum efficiency of the brain (EB) $_{max}$ becomes:

$$(EB)_{max} = 2.10^{50}.(1.38 \times 10^{-23}.3 \times 10^2.0.693)$$
$$= 5.7 \times 10^{29}\frac{J}{s} = 5.7 \times 10^{29} Watt$$

4. CONCLUSIONS

The Bremermann's limit is an upper limit of the information processing, it is restricted by a max-value which is connected with a gram of any matter, in this study, and it was shown for the brain's mass of 1350 gr. But it plays role of (weight) of any material. To determine, the upper limit in this meaning, there is no any importance of the material type, it is just related with the mass-energy relation of the relativity minimum energy spreading, during very short times of the quantum world.

For this reason, the computed value, it is general for any material of 1350 gr. However, the literature says that the processing limit of the brain cannot be greater than this limit. From this viewpoint, the Launder's limit is also became an upper limit in terms of the power or energy. These are the limits of the nature!

Finally, there is no any artificial or living thing can compute more than 2×10^{50} (or 2×10^{47})) of its mass. This is related with a self-contained system because the power (energy) supply is provided in the total mass and the computation is defined as an information transfer through one or more channels (like several Shannon's information channels) within the system.

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BIOGRAPHIES

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THE MULTIRESOLUTION WAVELET ANALYSIS OF THE BRAIN SIGNALS OF EPILEPSY PATIENTS

M. F.Ilaslan

Abstract – Wavelet transform is a new topic in signal processing. Its development and application remains an active and important area of research. In addition, the brain is the most vital organ of human. Trying to understand the brain means that trying to understand oneself. Thus, humans have tried to analyse and obtained some information about brain. However, its diseases are very hard to detect. This paper presents a tutorial introduction of the multiresolution wavelet analysis theory, implementation and interpretation of the wavelet transform about epilepsy disease. The paper concentrates on the application of the multiresolution wavelet transform to taking data from volunteers' electroencephalography (EEG) data. The method of Multiresolution wavelet analysis (MRWA) serves as a link between the discrete and continuous theory. Because of that, in that paper, that EEG data will be examined by using Multiresolution Wavelet analysis and it will be summarized how to defect the disease by using signal processing.

Keywords—*Wavelet, Multiresolution Wavelet Analysis, EEG, Epilepsy*

1. INTRODUCTION

THE brain, which is the centre of all our senses, thoughts, feelings, is a very soft piece of meat that has been settled in a hard skull. Besides its simple appearance, it is the most complex structure in the universe. It receives signals from the body's sensor such as kidney, lung, heart, and outputs data to the muscle then they realize the motions. The other mammal brains have the identical structure as human brains, but it is smaller in relation to body size than human brains.

The human brain acts as a communication system that is comprised of neurons. Neuron is a tiny nerve cell that is worked as transceiver by electrical signals from sensory cells that is called sensory neurons, over long distances within the body.

The importance of the human brain is that:

1. It regulates internal processes, which are most often involuntary such as heartbeat, dilation of pupil, involuntary contraction of muscles, and voluntary contraction of muscle as in smooth muscle contraction such as in the process of peristaltic movement [1].

2. It acts as an important part of the body system that enable cognitive processes like remembering, thinking etc. How the brain works is an important thing to understand because we are humans in possession of a brain.

3. It provides coordination of bodily activities so that there is a balance between the actual physiological responses and the anticipated physiological responses. For example, voluntary movement although voluntary, you do not take too steps at a time while working neither do you jerk. The action is a step by step forward sequential of backward sequential movement except you jerk or jump. Even if you are not currently thinking about working, you still have a part of your brain that coordinates orientation of the body in space (parietal cortex, cerebellum).

1.1. Main Parts of Brain

The cerebrum, cerebellum, and brainstem composed the brain. Cerebrum is the colossal piece of the brain. It contains right and left hemispheres. It achieves the important activities such as touching, hearing, interpreting, emotions, and well checking of functions [2].

Cerebellum is the last part that came to exist in the process of the evolution. It takes the data from Cerebrum and it coordinates muscular contraction, physical balance [2].

Brainstem as shown in the Figure 1. acts as a transhipment centre conjoining the cerebrum and cerebellum to the spinal cord. Breathing, warmth of body, sleep-wake cycle are completed successfully [2].

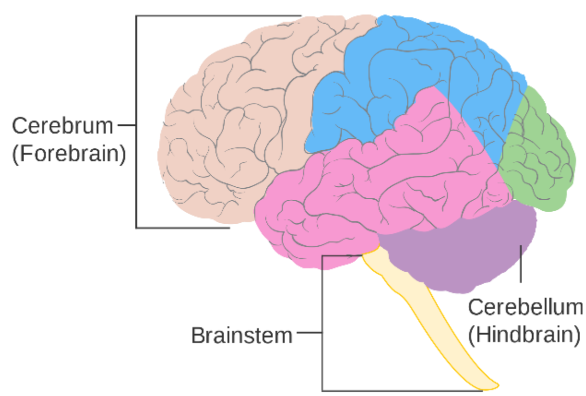

Fig.1. Main Parts of a Brain [10]

The Cerebrum is split in half: the right and left hemispheres. Latin name of fiber bunch is corpus callosum. It sends the messages and information from side to side. Each hemisphere checks and rules the converse part of the body. If a Paralysis occurs on the left part of the brain, your right part such as arm, leg etc. may be crippled [2].

1.2. Lobes of the Brain

The cerebral hemispheres has four lobes that are frontal lobe, temporal lobe, parietal lobe, and occipital lobe. Each lobes has

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different actions but the crucial point is that each lobes does not plough a lonely furrow. They have complicated relations [2].

Frontal Lobe: The tasks of judgement, planning, sexual impulses, behaviour, problem solving, and organizing the motor skills belong to the frontal lobe [3].

Parietal Lobe: It is responsible for sensory information that is collected in various parts of the body. Functions such as information processing, spatial orientation, speech, visual perception recognition, reading and writing are the tasks of the Parietal Lobe.

Occipital Lobe: It interprets the visual stimulation. Damaged occipital lobe may cause visual disturbances and hallucinations.

Temporal Lobe: Its functions are about understanding language, memory, hearing, sequencing and organization [2].

1.3. Brain Waves

The best explanation to understand the brain waves is that they are the models of electrical activities that occur inside the head. Brain waves are very important to all situations of brain functioning: behaviours, thoughts and emotions. SI Unit of Brain wave frequencies are Hertz (H). It means cycles per second. There are four ranges of brainwaves.

Gamma Brainwaves (38-42 Hz): Gamma brainwaves are the most vigorous waves in the spectrum. They have the fast brainwave frequency with a small amplitude.

Beta Brainwaves (14-30 Hz): They are characteristic of a linked mind, which is extremely alert and quite-focused. Beta function is fast-connect and activity. In addition, it is tendency to control the waking state of consciousness [4]. They are generally detected in the frontal lobes and it is seen on both sides of the brain.

Beta brainwaves are linked when the brain is awaken or processing functions such as solving hard problems, criticise of conditions or making a speech that aims to teach [4].

Alpha Brainwaves (9-13 Hz): Beta Brainwaves are faster than the Alpha Brainwaves. They show a relaxed awareness in the consciousness. Alpha is detected in the front part of the head. Alpha brainwaves are about relaxation like making meditation, imagination and intuitive thinking as convalescence from edgy thoughts [4].

Theta Brainwaves (4-8 Hz): They can indicate drowsiness, and the first phase of sleep or somnolence. Theta activities are commonly seen on children up to thirteen mostly in their sleep. They are about accessing subconscious information, half-awake half-asleep state, and attenuation in body rhythms, such as heart rate and breathing [4].

Delta Brainwaves (Below 4 Hz): They can explain deep sleep or thinking. They are in tendency to be the slowest waves with the highest amplitude [4].

Brain diseases can be in different forms. In addition, these diseases can be reasons of some disorders in different part of body such as paralysis, epilepsy. This paper will focus on that part of subject. The disease will be diagnosed more easily by analysing and comparing the data, which were taken from patient and healthy people.

Epilepsy is a brain disease caused by the deterioration of the standard activity of the brain because of abnormal electrical activity that occurs temporarily in the nerve cells. Epilepsy could be a conclusion of a medical injury or brain damage or other reasons. Some seizures that are dependent on tumour or bleeding in brain could be treated by surgery. In some cases, seizures can be treated by some medicines, in other cases are called refractory epilepsy. Also for some patients, vagus nerve stimulator (VNS) that is like cardiac pacemaker, inserted to patient by surgery. This device could decrease the number of seizures [5].

2. MULTIRESOLUTION WAVELET ANLAYSIS

The time-frequency resolution problems are originated by the Heisenberg uncertainty principle. A fixed time-frequency resolution is used to resolve for the STFT. A signal, which is at different frequencies with different resolutions, is analysed by Multiresolution Analysis (MRA). Multiresolution time-frequency plane is showed the change in resolution schematically in Figure 2 [6].

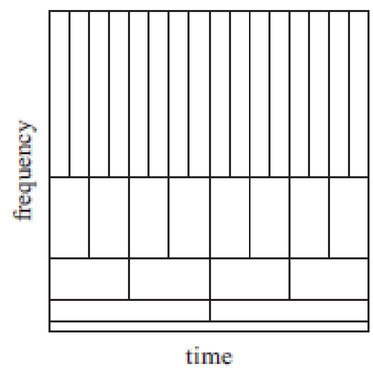

Fig.2. Multiresolution time-frequency plane [6].

According to Figure 2. it is assumed that low frequencies took place for the whole continuation period of the signal, and high frequencies appear from time to time small explosion. The wavelet analysis calculates the correlation between that signal and a wavelet function ψ (t). The resemblance between them is calculated separately in different time period. Thus, this representation ψ (t) is called mother wavelet [6].

Different frequency resolutions can be obtained.by making different scaling. Scaling and translating parameters can be established from wavelet and scaling function [7].

$$\phi_{j,k}(t) = 2^{\frac{j}{2}}\phi(2^{j}t - k) \quad (1)$$

$$\psi_{j,k}(t) = 2^{\frac{j}{2}}\psi(2^{j}t - k) \quad (2)$$

where j is the dilation parameter, and k is the position parameter. In application, whole data is wanted to see with desired resolution. Thus, the subspaces are defined [7].

$$V_j = Span\left\{\phi_{j,k}(t)\right\} \quad (3)$$

$$W_j = Span\left\{\psi_{j,k}(t)\right\} \quad (4)$$

Some necessities for multiresolution analysis are written below [7];

1. There is an orthogonal feature between the scaling function and its integer translates.

2. The subspaces at low scales are nested within spanned at higher scales.
3. The only common function for all V_j is $f(x) = 0$.
4. Representing function is optional.
For Haar scaling function

$$\phi(t) = \frac{1}{\sqrt{2}}\phi_{1,0}(t) + \frac{1}{\sqrt{2}}\phi_{1,1}(t) \tag{5}$$

Extend the notation of $\phi_{j,k}(t)$, we have

$$\phi(t) = \frac{1}{\sqrt{2}}(\sqrt{2}\phi(2t)) + \frac{1}{\sqrt{2}}(\sqrt{2}\phi(2t-1)) \tag{6}$$

That equation is called multiresolution analysis equation

$$\phi(t) = \sum_n h_\phi[n]\,\sqrt{2}\phi(2t-n) \tag{7}$$

$h_\phi[n] = \{\frac{1}{\sqrt{2}}, -\frac{1}{\sqrt{2}}\}$ is distinct for Haar scaling functions. Equation (7) means that $\phi(2t)$ is higher frequency function than the $\phi(t)$. It could be designed for discrete low pass filter $h_\phi[n]$ to have $\phi(t)$ [7].
Relation for the wavelet functions is that;

$$\psi(t) = \sum_n h_\psi[n]\,\sqrt{2}\psi(2t-n) \tag{8}$$

For Haar wavelets, $h_\psi[n] = \{\frac{1}{\sqrt{2}}, -\frac{1}{\sqrt{2}}\}$. Those two filters are connected with

$$h_\psi[n] = (-1)^n h_\phi[1-n] \tag{9}$$

A diagram that is Figure 3. shows the relationship between the sets and the functions [7].

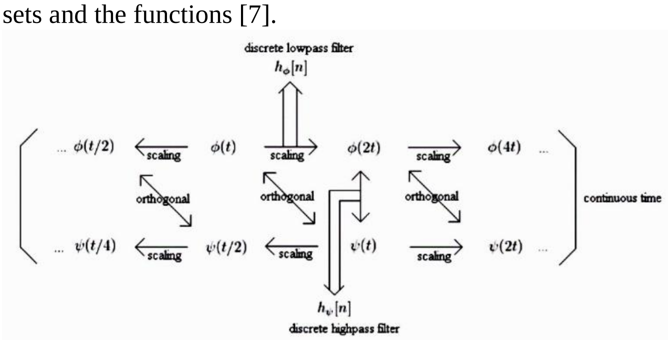

Fig.3. The relationship between scaling and wavelet functions [7].

We union infinite wavelet sets, the sets are equal to the L^2(R), set^2. This is requirement 4. In mathematical words, it is

$$L^2(R) = V_0 \oplus W_0 \oplus W_1 \cdots \tag{10}$$

Thus, any function in L^2(R) could be resolved, by benefitting from the scaling and wavelet functions. Similarity of that concept is like cross-section of a cabbage. When cabbage is cut in the middle, and looked, layers of leaves could be seen. Then if the one layer is taken from them, remaining part is will be cabbage but not the original one. This is the analogy of the scaling function at different scales with different supports but with similar shape [7].

3. APPLICATION OF MRWA TO THE BRAIN SIGNALS

First of all the data is taken from health and disease volunteers then they are shown in waveform. After that, that signals are analyzed by making multiresolution wavelet analysis. Finally, their results are compared and discussed. Volunteers' data is taken from reference [8].
Data_b: EEG Data of Healthy Person
Data_d: EEG Data of Seizure-Free Interval
Data_e: EEG Data of During Seizure

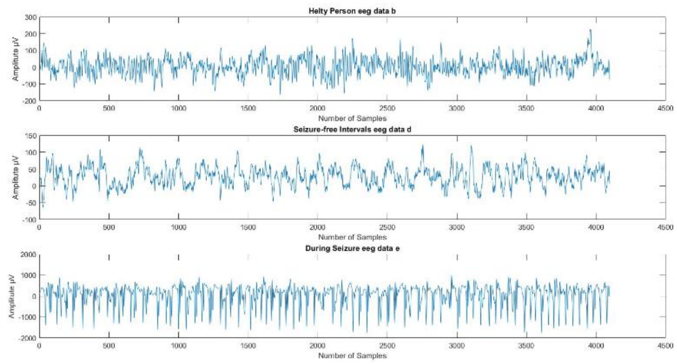

Fig.4. Waveform of Taken Data.

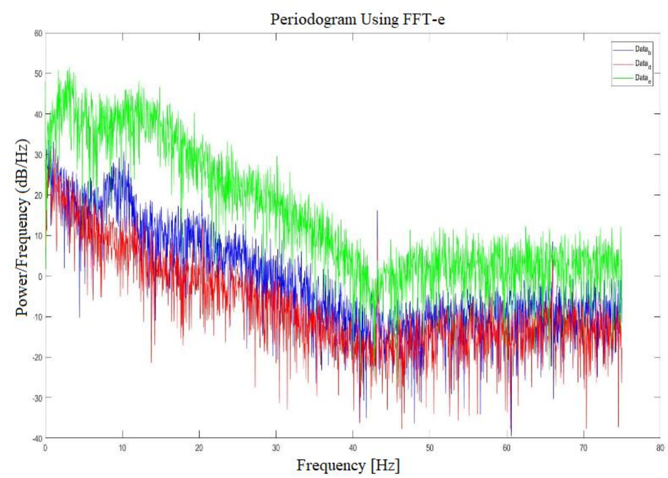

Fig.5. Imbricated Power Spectrum Density Graphs of Taken Data.

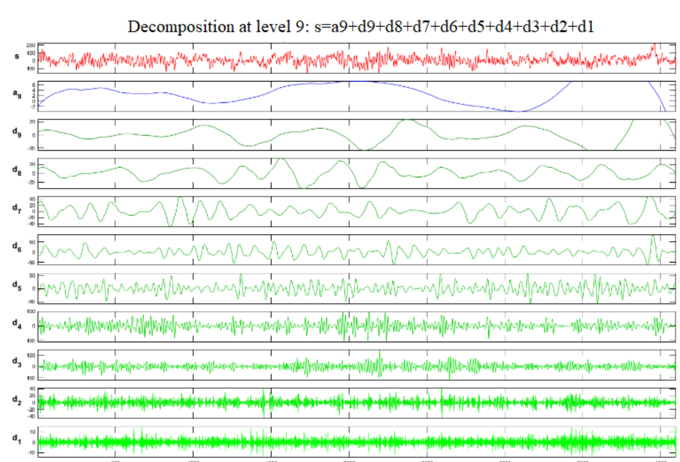

Fig.6. Multiresolution Wavelet Analysis of Data_b (Db-9).

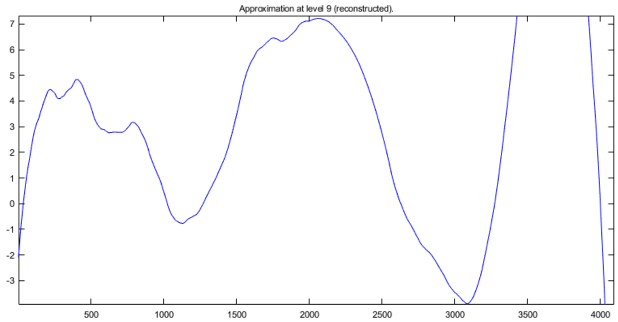

Fig.7. Approximation at level 9 of Data_b (reconstructed).

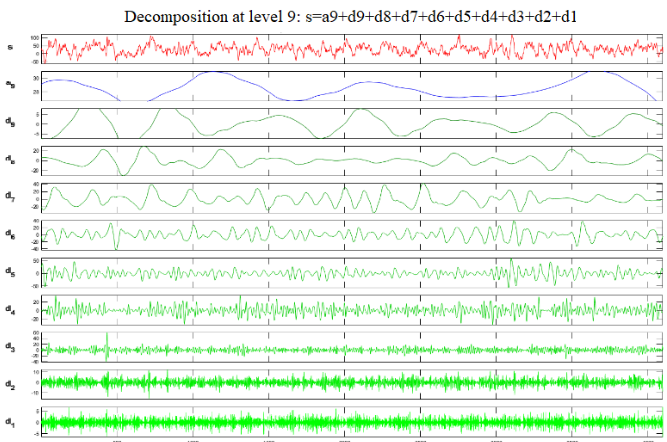

Fig.8. Multiresolution Wavelet Analysis of Data_d (Db-9).

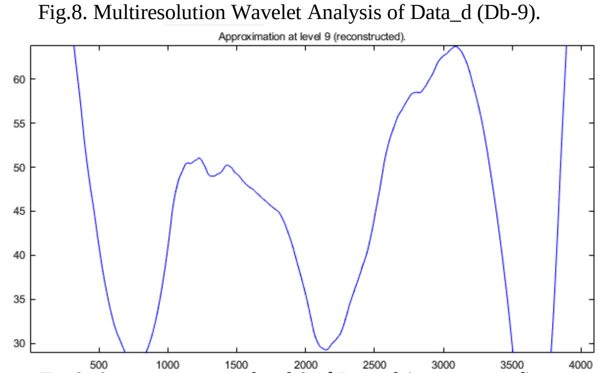

Fig.9. Approximation at level 9 of Data_d (reconstructed).

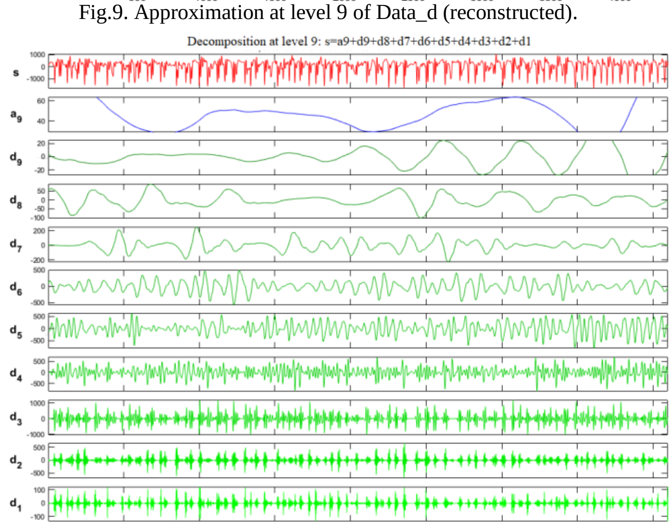

Fig.10. Multiresolution Wavelet Analysis of Data_e (Db-9).

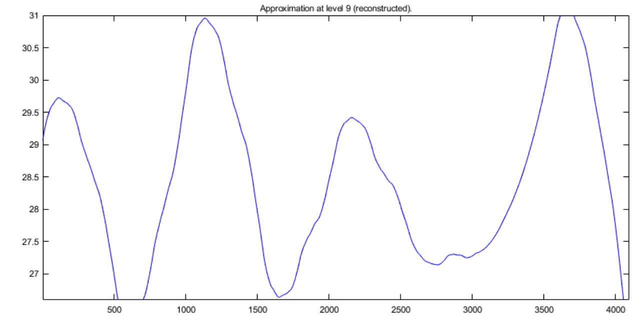

Fig.11. Approximation at level 9 of Data_e (reconstructed).

4. CONCLUSION

Wavelets Analysis is a method that analyse and process the signals that has carry data. It has a strong mathematical background. Wavelets Analysis has increased its popularity independently in the fields that study signal processing mainly such as seismic geology and disease analysis in the medical field. Continuous Wavelet Transform is a good method to analyse the signal, however when it comes to the reconstruction of the signal it might not be that good. Because of that, the given data is analysed by using MRWA is rather than CWT.

In this paper, data was taken from the healthy person's and epilepsy patient's was examined. Epilepsy patient's at the time of seizure data and at the time of normal data were taken. The collection and analysis of these data contains important information for diagnosis. First of all, statistical analyses have been done and then the signals were analysed. The results of the analysis of signals that are belonged to patient and healthy person, show that the constructed and reconstructed graphs help to make determinative interpretation to detect the disease.

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A NEW COGNITIVE SYSTEM MODELING WITH THE COMBINATION OF EXPERT AND NEURAL NETWORK SYSTEMS

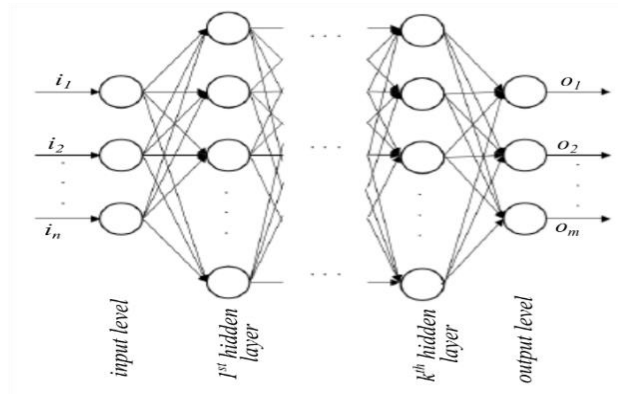
B. Alafi

***Abstract*—** In this paper definition of cognitive systems and its operation principle are mentioned. As a sequence, combination of expert and artificial neural network (ANN) is introduced as a cognitive system. In this approach, decision is taken by human based expert and these expert based information is coded and presented to a neural network system as a learning system. The procedure to be followed is simply described in the context. Then the algorithms of making a neural network as a cognitive system by logics from a human expert – which is a cognitive system – system are announced.

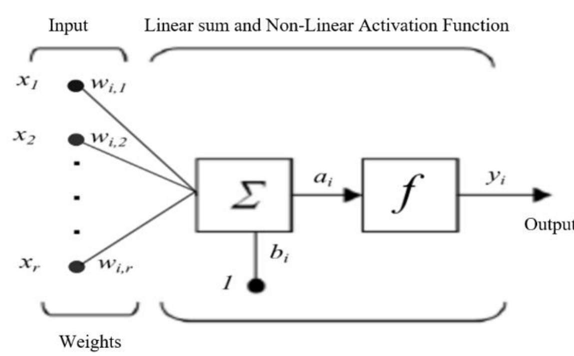
***Keywords*—** *Cognitive system, Neural network, Expert networks, Rule based networks, Learning system*

1. INTRODUCTION

THE human based expert is a concept which is defined as cognitive system. Transferring knowledge and experts from human to programs or learning systems will construct a knowledge based system which is considered as a cognitive one. Cognitive systems are playing a pivotal role in recent generation of science and technology. Since cognitive systems are the systems which learns, and thinks like human, a human based expert results a cognition in learning system via learning algorithms and logics. In order to distinguish desired conditions, at first human brain should determine all conditions and then classify them in different categories based on each phenomena parameter [1, 3, 4, 5]. Then all conditional logics (*If condition1 Then do procedure number 1*) can be obtained from this classification. To model and imitate the human brain sensing and acting ability, a structure which can learn and classify is required. Neural network can be an appropriate candidate for this purpose. Neural networks are learning systems without any mathematical operation which have been employing to obtain relationships between input and output pairs. Neural network is a system with main blocks of neurons. Information between input and output levels is stored in weight factors as hidden layers. Relevant model will be caught via weighted inputs which are collected together. Input layer is specified by received information from the system and then weighted properly based on error propagation algorithm. There are hidden layers by the task of applying system function for the problem. Then the outputs via error propagation maps to the hidden layer [1-2]. Topology of neural network is shown as figure1.



(a)



(b)

Fig.1. Neural Network structure. (a) Neural Network Topology. (b) Neural Processing Element

By means of this general procedure neural network is assumed as a learning system. This learning ability can be changed by the main topology of system which is depending on Problem type, input and output sizes, hidden layers, error propagation. Applying the neural network as a human inspiring system will make a cognitive system.

2. COGNITIVE SYSTEM

Mental system of human being is consisting a lot of interrelated items of knowledge, believes, ideas etc. which control his/her actions and determine how human being deal with received information from around world [3-7]. This system is determined as cognitive system. Cognitive systems simulate the human cognition process to find solution in different situations. Cognitive systems do not define as only programmed system, actually they can learn at scale and logic through interaction with human naturally and their own experience from ambient. Generally, cognitive systems are probabilistic, and deterministic one which not only can solve the numerical

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problems but also for prediction, meet argument, and recommendations about any type of information. The cognitive systems are probabilistic, it means they are programmed and designed to catch and figure out the type of huge amount of unstructured and complex data. Actually, programmable systems lead input information through some layers to reach the outputs. These systems are complex and powerful enough to catch the output via huge amount of input data and predict and determine the outcomes, but they are not capable to process unpredictable input. These systems act like human, as they can read text, see images, hear sounds, distinguish what they are reading, seeing, or hearing [6]. And through this procedure, they can organize and explain the received information. Despite these human liked abilities, they are not able to offer the definitive answers. They just are able to weigh received data from huge multiple sources and then process and offer hypothesis, or any other required data based on huge amount of information. To reach this purpose a cognitive topology is required. A cognitive topology is a kind of topology which overlaps with artificial intelligence technology which involves technologies such as expert systems, neural networks, robotics and virtual reality with the same base topology [3,5,6].

3. New design for cognitive system

Cognitive systems are not limited to a determined group of information sets; any system can be considered for this topology. Cognitive system achieved by human expert and neural network is described in this procedure; data coming from the system can be represented by means of the human based expert system – which acts as an operator – approach and then it is converted to “if … then … or if … and … then …” structure as a logical structure. This logical coding and then this data structure can be implemented to train the information through neural network. As a result, this new trained neural network plays the role of logic modeling. And this type of system can be used in engineering or any kind of systems as a cognitive system. A cognitive system algorithm flowchart is shown as figure2.

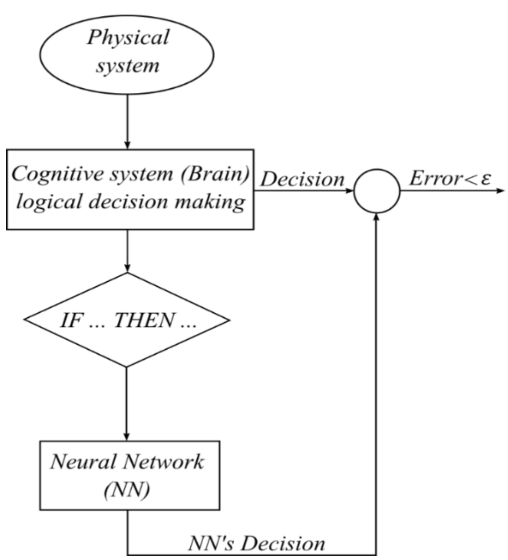

Fig.2. Cognitive system flowchart.

4. Conclusions

As shown in figure.2 the first block is related to cognitive or human based expert which is depending on the decision of the human based operator. The data can be coded in “if … then …” logics and it is represented by neural network. So its decision can be interpreted as a machine learning decision maker and assumed as a cognitive system.

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TRANSFER LEARNING BASED CLASSIFICATION OF SEGMENTED LANDING PAGE COMPONENTS

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***Abstract*—** The pages that appear in front of users on digital platforms used for online advertising to attract attention to target product are called landing pages. Landing pages aim to increase advertisement conversion rate using the metrics like clicks, views or subscribes. In this study, a method is presented to automatically classifier the most commonly used components on landing pages which are buttons, texts, and checkboxes. Landing page images given as inputs are segmented by morphological and threshold-based image processing methods, and each segment is classified using a Transfer Learning based method which combines pre-trained Inception v-3 networks and Support Vector Classifier (SVM). Furthermore, different classifiers were applied to compare the results. The proposed method is anticipated to be an essential step in the process of designing landing pages automatically with high advertisement conversion rates. Thanks to the proposed transfer learning based method, this is achieved by using fewer number of training data.

Keywords*—*Landing Page Segmentation; Transfer Learning; Image Processing; Image Classification.

1. INTRODUCTION

A LANDING page is a page specifically designed for a particular target audience or product, especially for being used in digital marketing activities. The purpose of these pages is to increase digital conversion rate by using metrics like clicks, views or subscriptions. Landing pages have designs that contain an aim and message intended for the target audience and affect the conversion rate. Landing pages that are inadequate in design and do not correspond the expectations of users lead to low conversion rates [1,16].
Designs of landing pages commonly consist of components such as buttons, checkboxes, texts, and pictures. A representative landing page with related components is shown in Figure 1.

To the best of our knowledge, there are a very limited number of studies to segment and classify the landing pages for online advertising [19]. However, there are many studies about image segmentation and classification in computer vision and image processing literature [2-4,6-11].

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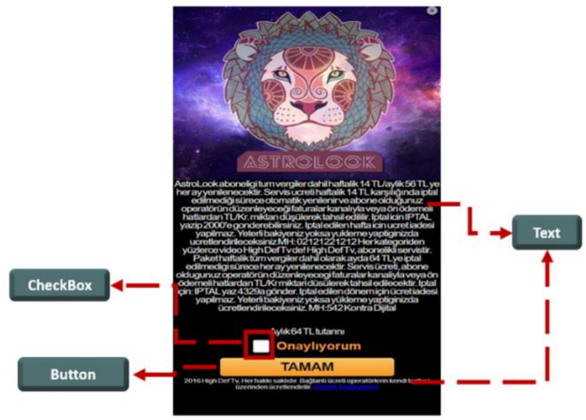

Fig.1. A representative landing page in online advertising and the most commonly used components of landing pages; "text," "checkboxes" and "buttons."

Among them, there exist studies on text detection in color images, as well [5-6]. Segmentation methods divide the image into components by using properties, such as, pixel density, color, texture, etc., [9]. The methods used for successful segmentation of the images differ [10]. Multiple image segmentation methods can be combined considering the ambiguity and variety of images [11].

Deep learning algorithms, especially Convolutional Neural Networks (CNN), have been widely used to classify images [23-25]. Even though CNN has acquired remarkable achievement in image classification [12-14], there have been some cases that image classification through CNN was not the proper approach. In particular, there may arise overfitting and convergence related issues when dataset sizes are too small to train a CNN model [26]. Due to increase in the performance of CNNs with massive datasets, network sizes have been increased in many studies with complex architectures [27]. However, the complexity of model may lead overfitting [18]. Consequently, domain adaptation and transfer learning based approaches may be utilized to mitigate overfitting problems [29,30].

Transfer learning, is a machine learning approach, which allows to use a pre-trained model for different tasks or domains [27-30]. In the literature, many studies having tasks with limited training data problem have utilized transfer learning [25]. Since it is allowed to use pre-trained models for the datasets from different domains, transfer learning is preferable for most problems where collection of data/data acquisition is difficult [25]. In this paper, transfer learning is deployed for landing page component segmentation, as the labelled dataset for landing page components is limited.

Due to the design limitation of these components, collecting a vast amount of data was a hard issue. In order to handle this problem, transfer learning including CNN and Support Vector Classifier (SVM) has been used. There are many studies combining CNN and support vector methods to classify images [21]. After extracting features from the images using CNN, performing classification by SVM yields remarkable results [20,21]. In some cases, it is observed that combining CNN and SVM performs better in image analysis than using either one of the methods [22].

2. LANDING PAGE COMPONENT CLASSIFICATION USING TRANSFER LEARNING

The proposed image analysis method to detect components of landing pages consists of two steps. In the first stage, landing pages obtained as digital images are segmented based on morphological operations and thresholding [19]. In the second stage of the proposed method, each image segment is assigned to one of the 'Button', 'Text', 'Checkbox' classes by SVM, which are the most common components of a landing page. The flow chart of the proposed method is presented in Figure 2 whose details are described below.

2.1. Detecting Landing Page Components with Image Segmentation

In this stage, the single channel gray level image (Y - brightness component) is obtained from the three-level Red, Green, Blue (RGB) image belonging to the landing page [15]. Morphological gradient operation is applied to the gray level image by using 3x3 dimensional elliptic structuring element in (1). Afterwards, Otsu thresholding is applied to the obtained gray level output image to binarize it.

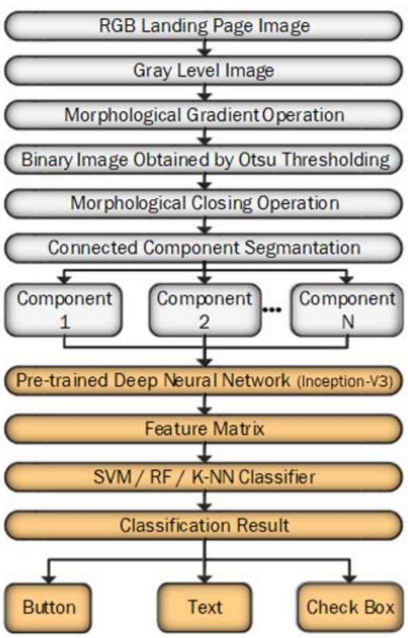

Fig.2. Steps of the proposed method to classify and segment the components of landing pages. Digital landing page images obtained as inputs are segmented based on morphological image processing operations followed by thresholding. Each candidate component obtained from segmentation is assigned to one of the 'Button,' 'Text,' 'Checkbox' classes, which are the most commonly used components in landing pages.

The binary image is separated into its candidate segments by using connected components after applying morphological closing operation. The 10x2 rectangular structuring element determined by the common features of the landing page components is used in morphological operation [17]. A sample landing page image is shown in Figure 3, while the candidate components of the same landing page is presented in Figure 4.

$$M = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}. \quad (1)$$

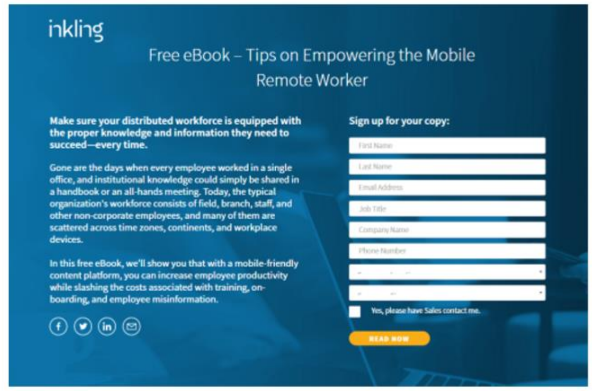

Fig.3. A sample landing page image

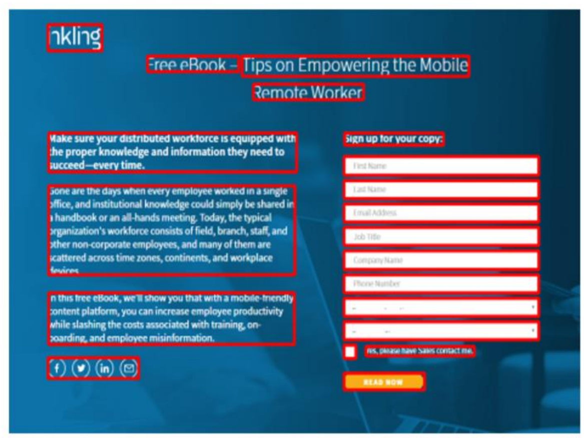

Fig.4. Candidate components of the landing page image in Fig. 3, obtained as a result of the processes in the first part of the proposed method. Respective components are assigned to one of the classes "Button", "Text" and "Checkbox".

2.2. Classification of Segmented Components with Transfer Learning Based Approach

In order to make the system automatically identify which one of 'button', 'text,' 'checkbox' classes do the segmented components belong to, a transfer learning-based approach including CNN and SVM classifier is used. First of all, the features were extracted from the images by using a pre-trained CNN network. Afterwards, different classifiers were trained for classification. From the results obtained, SVM Classifier was selected as the best performing classifier.

2.2.1. Feature Extraction

Inception-v3, one of the pre-trained deep learning models developed by Google, was re-used for our datasets consisting of segmented button, text and checkbox components of landing pages [28-30]. As the last layer (fully connected layer) of the Inception-v3 corresponds to the classification part of CNN model, it is eliminated from the architecture to establish different classification models instead.

Convolutional layers have been used to determine and extract the relevant features of images and classification has been carried out by fully connected layers in image classification using deep learning. In our study, the classification was carried out by transfer learning. Inception-v3 deep CNN model, which has been trained for ImageNet Large Visual Recognition Challenge using data from 2012, has been re-used for our dataset to extract features of size 2048 [28-30]. Since, the model has already been trained with a huge dataset, using its pre-calculated weights on a different dataset with small size as ours, has been very beneficial to easily extract features with a very small amount of time and cost. Inception-v3 model was used until it's last fully connected layer.

TABLE I
THE NUMBERS OF TRAINING AND VALIDATION DATA SETS BELONG TO EACH CLASS

Components	Number of Training Set	Number of Validation Set
Button	48	12
Checkbox	48	12
Text	56	14

The output obtained by the restricted Inception-v3 model has become the input that is fed to the SVM classifier.

The model was trained with the numbers of training data and validated using five-fold validation, as shown in Table I.

After the features acquired using Inception-V3 model, dimensionality reduction was applied to extracted feature vector by an unsupervised machine learning approach, t distributed stochastic neighbor embedding (t-SNE). Applying dimension reduction to the feature vector reduces dimension from 2048 to 2. Therefore, visualization of features in a lower dimensional space is provided (cf. Fig. 5). According to the figure, buttons (red), checkboxes (blue), and text (green) are well separated from each other.

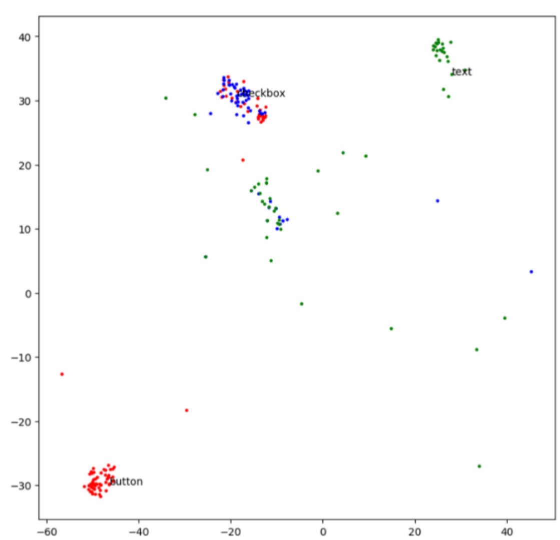

Fig.5. Demonstration of features in 2-dimension space by t - SNE.

TABLE II
ACCURACIES OBTAINED FROM SVM, KNN AND RF CLASSIFIERS ON VALIDATION SET

Classifier Type	Accuracy
SVM	97.6%
KNN	97.5%
RFF	96.6%

2.2.2. Image Classification

After extracting the features, each of SVM, Random Forest Classifier (RF) and K-Nearest Neighbors Classifier (KNN) were trained to classify and results were compared. For the output images obtained after the last pooling layer of Inception-v3 CNN model have set as inputs of related classifiers. For small-sized component datasets SVM yields better results than the other classifiers. Consequently, in our implementations, we utilize SVM.

3. EXPERIMENTAL RESULTS

In the second part of the proposed method, the Transfer Learning-based approach was performed after components of Landing Pages were segmented in the first part. Obtained components, which were segmented from the pages, are used as datasets in Transfer Learning. At first, the feature extraction was performed by pre-trained Inception v-3 model on this dataset. Secondly, classifiers including SVM, RF, KNN were trained on the extracted features of the dataset. After identifying features and their corresponding ground-truth labels, training was performed with 80 percent of the dataset being allocated as the training set while 20 percent of the is used as validation set.

The number of training and validation images is indicated in Table I and representative images used in training and validation sets are shown in Figure 6.

Fig.6. The representative images of button, checkbox, text classes used in validation and training data sets.

After performing classification using SVM, RF and KNN classifiers, it is observed that the best result was achieved by

SVM classifier with an accuracy of 97.6% Accordingly, SVM classifier has been determined as the final classifier to detect the class of Landing Page components. It is observed that the accuracy scores for the other classifiers are reasonably acceptable for a classification problem. Results of accuracies for each classifier are given in Table II.

4. CONCLUSIONS AND FUTURE WORKS

In this study, image analysis methods based on morphological operations, thresholding and transfer learning method based on CNN and SVM is presented to automatically segment the landing pages used in online advertising applications, to separate them into the three most commonly used components on the page and to recognize what the components are. In the proposed method, collected dataset for training is not an easy task because the components of landing page designs do not differ from page to page. The proposed method has prevented the problems related to small data.

For feature work, re-evaluation of the approach in such a way to classify the properties of the segmented components with respect to color, font, and size will be considered. Thus, the human factor in the designing process of the landing pages can be minimized, and the cost can be significantly reduced.

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CONTENTS

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