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CONTENTS

DEEP CONVOLUTIONAL NEURAL NETWORKS TO DETECT LUNG CANCER STAGE

H.S. Nogay

***Abstract*—**Regardless of the type of cancer, the treatment process starts after the staging process. The treatment method to be applied to the cancer patient depends on the stage of the disease. Therefore, all studies on the staging of cancer types have a big precaution. In this study, deep convolutional neural networks (DCNN) were used for staging of lung cancer. The TNM classification system is considered for staging. According to TNM, there are nine tumor stages in lung cancer. In the study, 200 data for each stage of lung cancer and 1800 MR images for 9 stages in total were used. As a result, a classification of 99.8% accuracy was performed in order to stage lung cancer with the proposed DCNN model.

Keywords*—Deep learning, Convolutional neural network, Lung cancer, Stage*

I. INTRODUCTION

LUNG Cancer is one of the most common cancer types in the world. It constitutes about one third of all cancer deaths. Only 15% of all lung cancers survive 5 years and more after diagnosis [1]. However, in the early stages this rate is quite high. It is necessary to know the stage of the disease for selection of treatment and prognosis in lung cancer. Clinical features, biochemical tests and radiographies of the patients are evaluated and stage determination is done by the staging methods. Pathologic examination is needed to classify lung cancer, to determine the level of invasion and to determine the surgical margins of the cancer [2,3]. Lung cancer is in 4 main stages. Computed tomography or magnetic resonance imaging for the abdomen or brain, bone scan (whole-body bone scintigraphy), PET, etc. are performed to determine the correct stage [4]. Some limited surgical interventions may be required to ensure complete staging.

Convolutional neural networks can be regarded as the most advanced state of machine learning approaches in recent years. There are many applications in the literature where convolutional neural networks are used. Conventional neural networks are used to solve image processing, medical image analysis and segmentation as well as classification and identification problems. Models in which the number of data and hidden layers are used much more are considered as deep learning approaches [5-8].

This study also used a convolutional neural network model that may be important in deciding on the treatment of lung cancer and may help to staging cancer. The study will shed light on the subsequent staging studies.

In the study, only the primary tumor part of the TNM staging system is based.

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II. MATERIALS AND METHODS

This study was based on the 'primary tumor' category in the 'Tumor Staging System' (TNM) classification. 9 stages were selected as DCNN output. The TNM Staging System is based on the extent of tumor (T), the extent of spread to lymph nodes (N), and the presence of metastasis (M).

Table I. TNM staging [9-11]

Primary tumor (T)	
Tx	No primary tumor detected
T0	No evidence of primary tumor
T1	Tumor keeps lamina propria, muscularis mucosa or submucosa
T1a	Tumor keeps lamina propria or muscularis mucosa
T1b	Tumor keeps submucosal
T2	Tumor keeps muskularis propriayı
T2a	Tumor subserosa retained, visceral peritoneum, no adjacent organ involvement
T2b	The tumor keeps the serosa (visceral peritoneum) and neighboring organs.
T3	The tumor keeps the serosa (visceral peritoneum)
T4	Tumor keeps neighboring organs

Table 1 shows the primary tumor part of the TNM classification. In the TNM classification, the 'T0' state shown in Table 1 was excluded when only the tumor condition was considered [9 -11]. Therefore, with the proposed DCNN model, the remaining 9 stages were tried to be estimated except the T0 in the staging system in Table 1.

The data set used in the study was obtained from the Cancer Imaging Archive (TCIA) website [12- 14]. In the study, 200 data were selected for each stage from image data of 5600 lung cancers and a data set consisting of 1800 data sets for 9 stages in total was used. In Figure 1, 1800 data from lung cancer patients in the dataset are randomly selected and presented as an example. The actual size of the images in the data set is 512x512 and consists of three channels and black and white colors in different tones. All image data is reduced to a size of 250 x 250 pixels for the model training period to be short. The sample dataset of 250 x 250 size consisting of random 36 data is shown in figure 2.

III. METHODOLOGY

In this study, a convolutional neural network model, which is accepted as the basic tool for deep learning, has been used [15]. The image data is automatically labeled according to folder names. This is done using the "imagedatastore" function in the MATLAB environment. The "imagedatastore" function also helps to efficiently read image stacks during storage of large image data, including data that does not fit in memory, and training of the deep convolutional neural network [16]. The original size of the image data used in the study is 512x512x3. Image data is reduced to the 250x250 size for 3 channels. There is no specific reason for choosing 250 pixels. A different dimension of 250 x 250 could be chosen, but in this case the training duration of the model will also change. In the study 200 data were used for each stage. A total of 1800 data were used for 9 phases. In the study, the data set is divided into two for each label. For each label, 75% of the data is allocated for training of the model. Thus, 150 data for each label were used in the training and the remaining 50 data were used in the test. The maximum epoch 30 and initial learning rate 0.0001 were selected as training options. Figure 3 shows the proposed DCNN model.

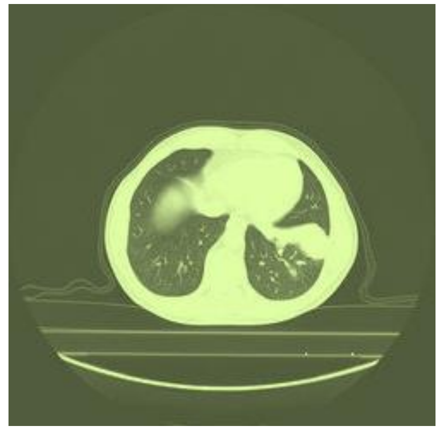

Fig. 1. MR image sample of lung cancer

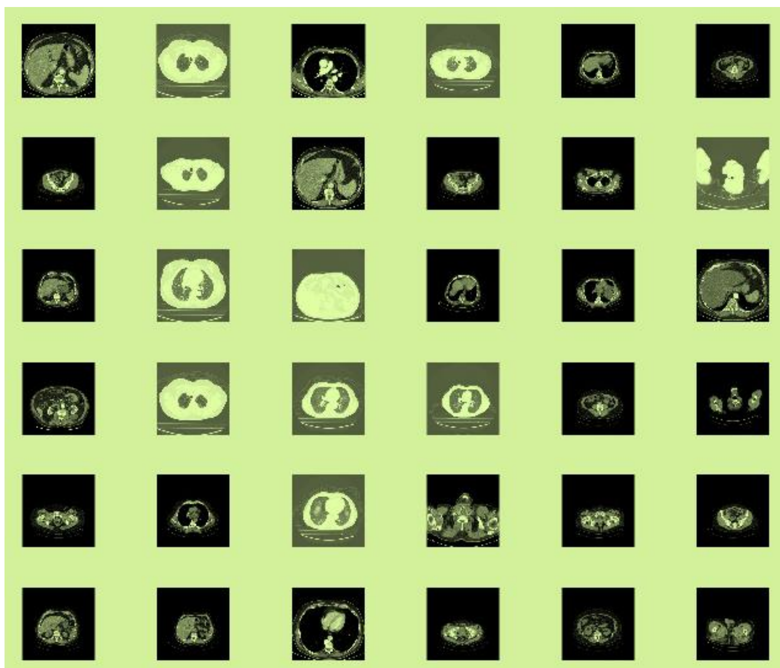

Fig. 2. Randomly selected sample dataset from real dataset

The following layers are used in the DCNN model:

Input layer: At the input layer, the real image data is reduced to 250 x 250 and presented to the next layer, the convolutional layer.

Convolution layer: In the convolution layer, it is very important that the training function uses the size of the filter and how many it is used when scanning. Three convolution layers were

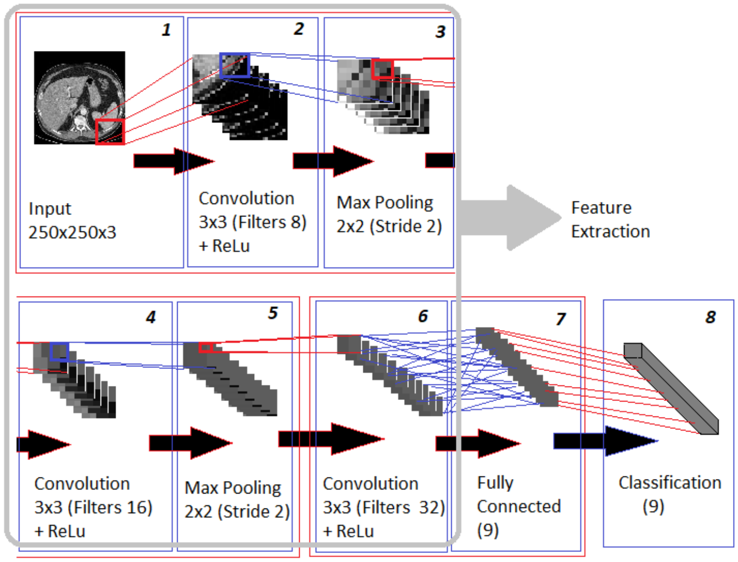

Fig. 3. Proposed DCNN model

used in this study. As shown in Fig. 3, in the convolutional layer used in section 2, 8 filters of 3 x 3 dimensions are used. In the convolution layer used in section 4, 16 filters were used in the same dimension and 32 filters were used in the convolution layer in section 6. The number of filters specifies the number of feature maps [16, 17].

ReLu layer: The nonlinear activation function follows the convolution layer. Since the study was performed in MATLAB environment, "rectified linear unit function" (ReLU) was chosen as the activation function.

Max-pooling layer: There is a max-pooling layer (along with the activation function) after the convolution layer, as a way of preventing the model's memorization and at the same time reducing the number of model parameters. In the 'Max-pooling' process, a rectangular frame is strided step-by-step over the entire view of the convolution layer. For each stride, the maximum number of numeric values on the image is taken. The rectangular frame is chosen as 2x2 and 2 squares in the 3 and 5 divisions [16-18], as can be understood from figure 3.

Fully connected layer: Usually one or two fully connected layers are used after the convolution layers. One 'fully connected layer' was used in the study. All neurons in the 'Fully connected layer' are connected to neurons in the previous layer. This layer combines all of the features (local information) learned by previous layers to define larger patterns. For this reason, the "OutputSize" parameter in the last fully connected layer is equal to the number of classes in the target data. In this study, the output size is 9, corresponding to 9 stages. The 'softmax' activation function is used to classify at the fully connected layer [16-18].

Classification layer: Last layer. This layer uses the probabilities produced by the softmax activation function for each input to mutually assign them to specific classes [16-18]

IV. Results

As a result of the test made, the accuracy rate for classification was 0.9889. Table 1 shows the training process of the model. As shown in Table 1, 100% mini batc accuracy was obtained at 410.14 seconds in the 30th epoch. And at the 30th epoch, the minibusc loss is very close to zero with 0.0112.

Table II. Training process of the DCNN model

Epoch	Iteration	Time Elapsed (seconds)	Mini-batch Loss	Mini-batch Accuracy (%)
1	1	15.63	2.1997	7.81
5	50	84.57	2.1809	24.22
10	100	147.85	1.8129	25.78
15	150	211.38	0.836	72.66
20	200	276.42	0.1005	97.66
25	250	343.48	0.1028	99.22
30	300	410.14	0.0112	100.00

The graph in Figure 4 gives the error of the testing process. In Figure 5, the accuracy of the model is given in the testing process.

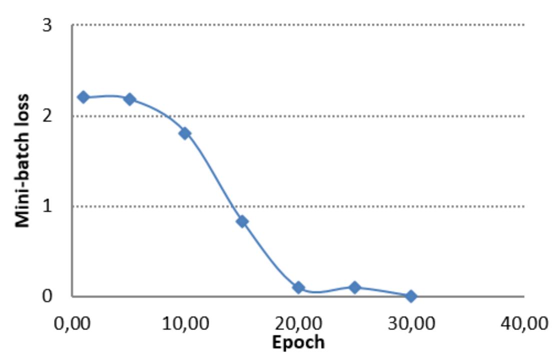

Fig. 4. Mini-batch loss for testing

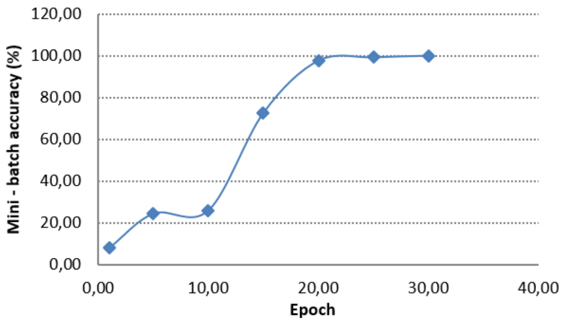

Fig. 5. Mini – batch accuracy for testing

V. CONCLUSIONS

The real size of the images used for the data set in the study is 512x512. For training and testing of the proposed DCNN model, the image data in the data set is reduced to 250x250 pixels in the first phase. Normally, in simple classifications, much lower data is used. For example, image classification is often used 28 x 28. However, the estimation and / or classification of the stage of lung cancer is an extremely sensitive issue, so the picture size has not been reduced much. The goal is to achieve a very high accuracy rate. The 30 epoch limit can be thought of as too much. As a result, as Table 2 reveals, the thirtieth epoch was reached at the end of 410.14 seconds. This duration seems to be longer than normal, but the accuracy rate of 0.9948 is quite satisfactory. In the last epoch, the lowest error rate was obtained, quite close to zero. This study has produced very successful results in terms of shedding light on more extensive studies in the future for staging other cancer types or including other staging categories.

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BIOGRAPHIES

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FUZZY EXPERT SYSTEM FOR SEVERITY PREDICTION OF OBSTRUCTIVE SLEEP APNEA HYPOPNEA SYNDROME

C. Zoroglu, and S. Turkeli

***Abstract*—** Polysomnography (PSG) is standard for both OSAHS diagnosis and severity detection, but it has some disadvantages such as requirement for many equipment, conditions and times to get successful measurements. The aim of the study is to design a fuzzy expert system (FES) to predict the severity degree of obstructive sleep apnea hypopnea syndrome (OSAHS). Pre-operation data of 24 patients who had robotic surgery for treatment of OSAHS are used. We divided the data into two: 14 of them for designing the FES and 10 patient data for testing the model. min SpO_2,, BMI, Mallampati score, and neck circumference (NC) information are used as inputs of the system. The output is fuzzified apnea hypopnea index (AHI). Then, this prediction compared with the actual AHI scores of the patients. Classification accuracy for design step is 100% and correlation between our prediction and AHI is 0.89 after removing 4 patients because of missing data. For the test result, classification accuracy is 100% and value of correlation coefficient is 0.82 after leaving one out due to same reason. Our study shows a possibility of simpler alternative to PSG and proposes fuzziness in standard AHI intervals as different point of view.

***Keywords*—** *fuzzy expert system, severity detection, prediction, Obstructive Sleep Apnea Hypopnea Syndrome*

I. INTRODUCTION

OSAHS is an important health problem which results from repetitive obstructions in upper airways. In apnea, respiration completely arrests whereas airflow partly continues in hypopnea [1]. Arrests or reductions in airflow lead to oxygen desaturation in blood, and this in turn, causes arousals. Insufficient sleep may lead to daytime sleepiness, fatigue and even traffic and occupational accidents [2]. Also, it is detected that OSAHS is related to arterial hypertension, hypercoagulability, reduced cerebral perfusion, atherosclerosis, cardiac arrhythmia, coronary artery disease, congestive heart failure, ischemic stroke, axonal peripheral neuropathy and diabetes mellitus [3]. Prevalence of the disease is 4% among middle-aged men, and 2% women in the same age category [4] It is predicted that these ratios increase for 65 age and older [5].

OSAHS is diagnosed and graded by analyzing some physiological parameters such as brain and heart signals, oxygen saturation, airflow, respiratory movements which are obtained in sleep laboratories by means of PSG. Laboratory tests alone are not sufficient for diagnosis. Results must be interpreted by experienced staffs. However, manual scoring of the resulting recording entails too much effort and time to the medical specialists and as a consequence it implies a high economic cost [6]

Among the parameters which are obtained via PSG, AHI is the key one for case identification, for quantifying disease severity. It is defined as the number of apneas and hypopneas per hour of sleep. Cases are graded according to AASM 1999 criteria as follows [7]: AHI<5 and ≤15 as mild; AHI>15 and ≤30 as moderate; and AHI >30 as severe. There are 3 standard hypopnea definitions published by AASM in different years. AHIChicago requires either > 50% airflow reduction or a lesser airflow reduction with associated > 3% oxygen desaturation or arousal. Hypopnea is defined as 30% or more airflow reduction with ≥ 4% desaturation in AHIRecommended. For AHIAlternative, hypopnea is defined as 50% or more airflow reduction with ≥ 3% desaturation or arousal. The cut-points given above are for AHIChicago, and they are used as a standard. However, when these cut-points are not adjusted for other definitions, it is found that approximately 40% of patients previously classified as positive for OSAHS using AHIChicago being negative using AHIRecommende and 25% being negative using AHIAlternative [8]. This indicates the need for more flexible AHI intervals rather than crisp ones.

Expert systems are used for decision making in various fields such as agriculture, chemistry, space technology, geology and medicine [9]. The basic idea behind ES is to transfer the vast body of task-specific knowledge from a human to a computer. This knowledge is then stored in the computer and users call upon the computer for specific advice as needed. The computer can make inferences and arrive at a specific conclusion. Then like a human consultant, it gives advices and explains, if necessary, the logic behind the advice [10]. Zadeh's introduction the fuzzy sets enable to use both numerical and linguistic variables together, and provide expert systems with the ability of human-like reasoning. Therefore, ES can be solution for the problem uncertainty in medical data and its classification which arises from the complex nature of medicine.

The aim of the study is to design a FES to predict the severity degree of OSAHS. Determining OSAHS severity is important because first, it is also an indicator for some of serious health problems such as heart diseases, hypertension and second, there is need for measures to evaluate treatment response. The system uses body mass index (BMI), minimum blood oxygen saturation level during sleep (min SpO_2), Mallampati score and NC as input. Then, we assigned each patient to one of three groups; mild, moderate and severe according to our OSAHS severity predictions. Normal health condition is not considered because the data consist of OSAHS diagnosed patients. Finally, output (i.e. severity of OSAHS) evaluated using AHI and the model tested on the data of another patient group which are not included in design process of the FES.

II. RELATED WORKS

This section includes some of past and current studies about medical applications of FES and the studies which specifically aim to help decision making problems about OSAHS.

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Developments of expert systems in medicine began with the MYCIN system about a decade after Zadeh's introduction of fuzzy logic. Although fuzzy logic was not used in MYCIN, the major role played by uncertainty in medical decision-making is recognized. One of first successful applications of fuzzy logic in medicine was CADIAG where the medical information is derived from medical records taken from a hospital information system. The information is fuzzified and coded in terms of rules. The system uses fuzzy logical inference mechanisms to generate diagnostic information. SPHINX and CLINAID are also early expert systems which utilize fuzzy logic [11]

The success of fuzzy logic for handling uncertainty in medicine and the results obtained when it is used in expert systems causes FES to be utilized in various fields of medicine. Castanho et al., used genetic-fuzzy system to predict the pathological stage of prostate cancer [12] Abdullah et al., used FES for hypertension risk prediction using age, body mass index (BMI), blood pressure and heart rate as input [13]. Riberio et al., evaluated breast cancer risk through age, menopause age, presence of hormone replacement treatment and fuzzy BMI. Then, they expressed the cancer risk by the terms which are moderate, high and very high [14]. Neshat et al., determined liver disorder intensity using BUPA Liver Disorder dataset which contains 345 male patients with 6 numeric attributes [15] Lee and Wang developed an ontology-based FES for diabetes decision support application. This system includes a five-layer fuzzy ontology, fuzzy diabetes ontology, and a semantic decision support agent [16]

Keleş et al., designed neuro FES for diagnosis of breast cancer using data which include 516 benign and 445 malignant masses with 6 features. In neuro FES, as distinct from FES, rules are formed by learning algorithms such as artificial neural network. Also, a user interface is designed to provide ease of use [17]. Oladele et al., used Adaptive Neuro Fuzzy Inference System (ANFIS) for malaria diagnosis. For each patient, an array whose values consist of 1's or 0's according to patient health status is formed. These arrays are inputs of the system and when a person diagnosed as malaria, output is 1, otherwise 0. A hybrid learning algorithm in which both supervised and unsupervised learning algorithms are used together is employed [18].

Allahverdi et al., determined 10-year risk of coronary heart disease for a patient using age, cholestrol level, high density lipoprotein (HDL) level and blood pressure data. Gender and smoking are also important factors but since they have binary values, instead of using them as input, four rules are constructed for all possible situations. According to calculated risk value and level of low density lipoprotein (LDL), system recommends one of three alternatives to physician: 1. patient can keep his/her normal life; 2. change in the diet is required; 3. drug therapy must be applied [19]. Ali Keleş and Aytürk Keleş used a neuro FES (called ESTDD) to diagnose thyroid disease. Data which consist of 215 sample, 3 classes and 5 features are used. The system has also a user interface and a database which stores patient information. Results show that the accuracy of the system is 95.33%. ESTDD can also be used for educational purposes. Randomly selected medical data belongs to each patient is showed on the screen and ESTDD system wants user to diagnose all patient or patients selected by educator. As a result ESTDD system compares user diagnosis with self-diagnosis and real diagnosis if it is previously entered in system and this statistical evaluation is showed at the bottom of the screen [20].

Fuzzy control applications are very common in anesthesia. These studies include monitoring of vital parameter of patients and controlling the drug infusion to maintain the anesthetic level constant. Some of these studies are controlling depth of anesthesia, muscle relaxation, prevention of hypertension during anesthesia and post-operative control of blood pressure. Pump-like function of heart makes it suitable for fuzzy control applications. A fuzzy controller has been implemented for adaptation of the heart pump rate to body perfusion demand by pump chamber filling detection [21]. Another more advanced system, which is based on neural and fuzzy controller for artificial heart, was developed by Lee et al. [22]. Fuzzy control is also used in artificial pancreas studies which play role in the treatment of diabetes. Atlas et al., applied fuzzy logic theory in their artificial pancreas in order to imitate lines of reasoning of diabetes caregivers. This system uses a combination of control-to-range and control-to-target strategies to automatically regulate individual glucose levels [23]

Steinman et al., proposed a framework to track disease stages. The model considers that a disease does not leaps from one state to the next, discretely and without any indication of the forthcoming event, rather, most transitions take their time, taking place gradually and continuously. Therefore, fuzzy sets become appropriate for modelling [24]. Becker et al., proposed an intelligent patient monitoring and alarm system which evaluates a patient's hemodynamic state on the basis of a current vital parameter constellation with a knowledge-based approach in order to support intra-operative monitoring for the anesthesiologist [25]. Keeping the oxygenation status of newborn infants within physiologic limits is a critical task. For this purpose several vital parameters are supervised routinely by monitors, such as electrocardiograph, transcutaneous partial oxygen pressure monitor and pulse oximeter. Each monitor gives an alarm signal whenever an upper or lower limit of the parameter measured is exceeded. However, a considerable amount of false alarms is generated by artefacts, which are attributed mostly to movements of the infants. Wolf et al., developed an automated system based on fuzzy logic to solve this problem [26].

Philips et al., applied a breath test for volatile organic compounds as a predictor of breast cancer to three groups. First two groups consist of asymptomatic women with abnormal mammograms, 51 with and 50 without histologic evidence of breast cancer in a breast biopsy, and third group of 42 age-matched healthy women with no history of breast cancer. Using Interrelation Miner fuzzy logic software, women with breast cancer and age-matched healthy volunteers were randomly assigned to a training set or a prediction set. Having determined the typicality matrices for both controls and breast cancer patients, these matrices are used to calculate the membership degrees of healthy and diseased states. The difference between these memberships degrees are used for breast cancer prediction. The predictive model was tested in the women with abnormal mammograms and no histologic evidence of breast cancer in a breast biopsy. Results show that this model is superior to the discriminant analysis model the authors previously reported [27]. Seker et al., did a study about prognosis which is critical for planning of treatment during different stages of diseases. In the study, fuzzy–nearest neighbor classifier is used to provide a certainty degree for prognostic decision and assessment of the breast cancer markers, and compared with logistic regression and multilayer feedforward backpropagation neural networks. The overall results indicate that the FK-NN-based method yields the highest predictive accuracy, and that it has produced a more reliable prognostic marker model than other two methods [28].

FES is also used for the determination of obstructive and other sleep apnea types. Bonillo et al., diagnosed sleep apnea syndrome by analyzing airflow signal, respiratory movement signals (both thoracic and abdominal) and oxygen saturation in arterial blood. To this end, signals are firstly preprocessed to reduce false positives by determining artifacts in the signals. Possible apneic events are determined according to drops in the amplitudes and interval lengths of the signals. Existence of an apneic pattern is considered when the underlying cause has physiological significance. Physiological events are thought as indicator of apnea, when they occur in a temporal order. Then, apneic patterns are classified as apnea, hypopnea or false positive using fuzzy inference system. In this system, firstly, oxygen desaturation signal of the pattern is evaluated and membership degree for desaturation concept is established with respect to duration and reduction of the desaturation signal. Next, airflow and respiratory signals are evaluated in the same way, and then combining these two results under some rules gives membership degrees for apnea, hypopnea and normal respiration. If the membership degree of normal respiration is less than the others, then this pattern is called apneic event. Lastly, respiratory movement percentage information when an apneic event occurs is used for determining type of sleep apnea [29]

Nazeran et al., developed to detect obstructive sleep apnea by using the respiratory airflow signal in adults. This signal is subjected to a series of processing step, and then areas and standard deviations are calculated for 3-second intervals. Since ranges of these values vary between patients, they are normalized by dividing the areas and standard deviations which are obtained from the first 60 or 120 seconds of normal breathing signals from each patient. Normalized areas and standard deviations are used as the inputs of the fuzzy systems. Membership functions of these inputs are derived from apnea and hypopnea events of four patients. Mamdani method is used for fuzzy inference. Lastly, the centroid method was utilized in the defuzzification stage to give the final crisp outputs [30]. Aims of this and former studies are to detect apnea/hypopnea events from physiological signals and to help or to automatize the scoring process. Nevertheless, the two studies require for PSG device. Polat et al, classified OSAS patients with respect to degree of disorder using ANFIS and one against all method. The parameters which are obtained from PSG are arousals index, AHI, min SpO_2 in stage of REM, and percent sleep time in stage of oxygen saturation intervals bigger than 89%. Role of one against all method is to solve the problem of dealing with multi class since ANFIS alone gives output with one class [31]. This study also uses only PSG data and its success heavily depends on the PSG success.

There are some studies which uses equations to predict OSAHS probability and sleep apnea clinical score. These models utilize self-reported OSAHS symptoms combined with demographic and anthropometric variables to discriminate between patients with and without OSAHS. Rowley et al., studied the utility of four clinical prediction models for either predicting the presence of obstructive sleep apnea (OSA, apnea-hypopnea index, or prioritizing patients for a split-night protocol and found that these models were not be sufficiently accurate to discriminate between patients with or without OSAHS but could be useful in prioritizing patients for split-night PSG [32]. Some studies attempted to predict AHI from nocturnal pulse oximetry measurement due to simplicity of its application with respect to PSG. Magalang et. al., compared the relative usefulness of the different indexes derived from pulse oximetry in the diagnosis of obstructive sleep apnea, and to determine if a combination of these indexes improves the prediction of the apnea-hypopnea index (AHI) measured by polysomnography [33]. Marcos et. al., estimated AHI by extracting time-domain and frequency-domain features from oximetry data and constructed relationship between these features and actual AHI using multiple linear regression and multilayer perceptron [34]. However, these methods are focusing only on oxygen saturation data which is actually determined or affected by risk factors of OSAHS such as obesity, tonsil size.

III. REASONS OF NEED FOR FUZZY LOGIC IN MEDICINE

Although it had been studied since the 1920s, as infinite-valued logic, the term fuzzy logic was introduced with the 1965 proposal of fuzzy set theory by Lotfi A. Zadeh [35]. As distinct from the classical (crisp) sets which use 0 and 1 to represent membership of an element, in fuzzy sets a degree of membership, which is in the interval [0, 1], is assigned by a membership function. For instance, 400C can have membership degree for both “moderate temperature” and “high temperature” fuzzy sets. This assigning process depends on application. As seen from the example, fuzzy sets make it possible to use natural language in computations. We generally use vague terms such as cold weather, high fever, etc. to express our daily problems. The power of fuzzy logic lies here: it provides human-like reasoning to solve problems. There are some sources of uncertainty in medicine which make appropriate the use of fuzzy logic [36]:

- The medical history of the patient is given by the patient himself. It is highly subjective and may include simulated, exaggerated, or understated symptoms.
- Indications can be misinterpreted because the boundary between normal and pathological status is not always clearly defined.
- Measurement errors, organizational problems (mislabeling samples, sending them to the wrong laboratory, etc.) may occur in laboratory tests.

IV. METHOD

This research was performed in accordance with relevant guidelines and regulations, adhered to ethical research standards set by the latest revision of the Declaration of Helsinki, was approved by Bakırköy Dr. Sadi Konuk Training and Research Hospital Department of Otolaryngology, and informed consent was obtained from all subjects. In this study, pre-operation data of 4 female and 10 male patients who had robotic surgery for treatment of OSAHS are used. All individuals were diagnosed as OSAHS after PSG. We used min SpO_2, BMI, Mallampati score, and NC information as input to predict OSAHS severity and compared the result with AHI scores of patients. Also, we tested our FES with 10 patients (two of them are women) which were not used in design process. Table I summarizes patient information for design and test group. We did not use Epworth Sleep Scale (ESS) because there is no significant correlation between the ESS score and the AHI [37] and age, since the relation between age and severity is not certain [1]. In the following, some concepts are defined. Then, design process of FES is explained as well as providing some fuzzy logic background.

Table I. Summary of patient information.

	Design	Test
Number of patients	14	10
Age	52±7.42	50±8.12
min SpO_2	82.4±7.84	77.8±6.27
BMI	32.5±5.48	28.5±5
ESS	11±4.6	13.6±1.43
NC	41±3.22	40±2.86
AHI	28±18.28	26.9±12.47

Definitions

Apnea: It is the cessation of airflow at least 10 seconds.

Oxygen desaturation: It is the reduction of blood oxygen saturation below the 90% or dip into 3% or more from the baseline. Baseline is defined as the mean amplitude of stable breathing and oxygenation in the two minutes preceding onset of the event (in individuals who have a stable breathing pattern during sleep) or the mean amplitude of the three largest breaths in the two minutes preceding onset of the event (in individuals without a stable breathing pattern) [7].

Mallampati score: The score is assessed by asking the patient to open his or her mouth as wide as possible, while protruding the tongue as far as possible. A standard I to IV grading system is used (Figure 1).

Fig. 1. Mallampati airway classification. Class I: soft palate and entire uvula visible; Class II: soft palate and portion of uvula visible; Class III: soft palate visible (may include base of uvula); Class IV: soft palate is not visible. C. Z. drew the figure.

FES Design

Typical FES architecture is shown Figure 2. In the following, components of our FES are examined. All these steps are performed using the Fuzzy Inference System (FIS) tool of Matlab version of R2013a.

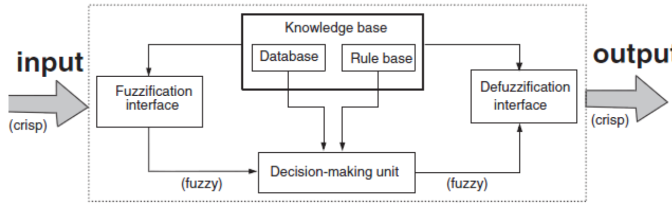

Fig. 2. Fuzzy system and its components[38].

Fuzzification

Fuzzification is the process where the crisp quantities are converted to fuzzy (crisp to fuzzy). By identifying some of the uncertainties present in the crisp values, the fuzzy values are formed. The conversion of fuzzy values is represented by the membership functions. Figure 3, 4, 5, 6 and 7 shows fuzzified inputs of min SpO_2, BMI, Mallampati score, NC and the output.

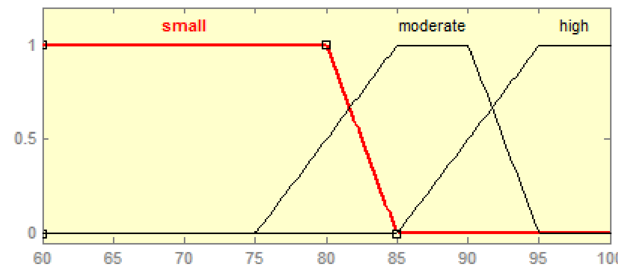

Fig. 3. Membership functions and corresponding linguistic variables of 'min SpO_2'.

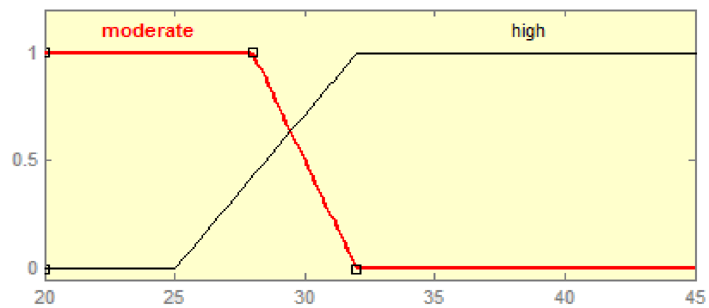

Fig. 4. Membership functions and corresponding linguistic variables of 'BMI'.

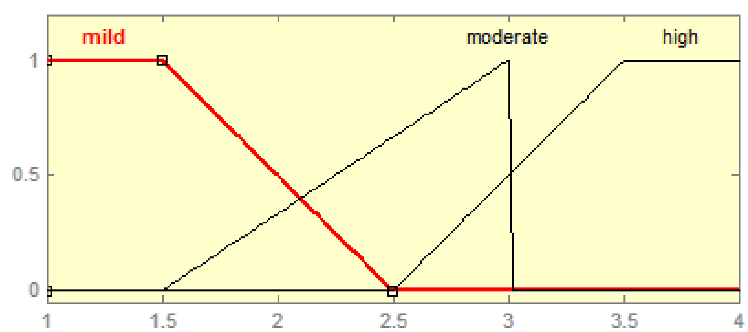

Fig. 5. Membership functions and corresponding linguistic variables of 'Mallampati score'.

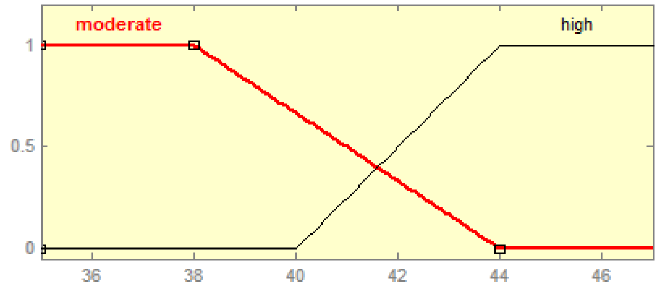

Fig. 6. Membership functions and corresponding linguistic variables of ‘NC’.

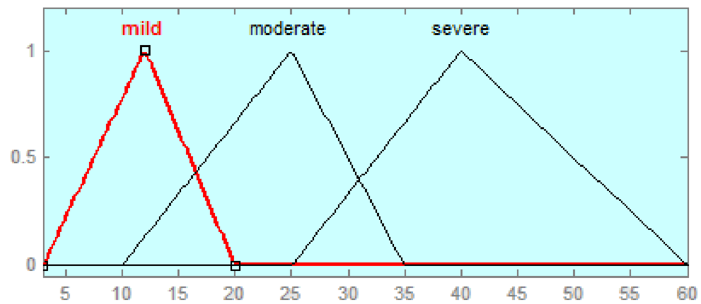

Fig. 7. Membership functions and corresponding linguistic variables of ‘Severity’.

Construction of Rules

Rules are the required components together with the inputs to inference. They are in the form of “If x is A, Then y is B”. Here, x and y are the linguistic variables, A and B are the linguistic terms. “If” part of rule called antecedent, and “Then” part is called consequent. Rules are formed either by consulting a domain expert or based data using methods such as artificial neural network or genetic algorithm. Since our data is not sufficient for the latter ones, we constructed the rules by referring otolaryngology experts. Figure 8 shows the formed rules.

1. If (SpO is small) and (BMI is high) then (Severity is severe) (1)
2. If (SpO is moderate) and (BMI is high) and (Mallampati is moderate) and (NC is high) then (Severity is severe) (1)
3. If (SpO is small) and (BMI is moderate) and (Mallampati is high) and (NC is high) then (Severity is severe) (1)
4. If (SpO is high) and (BMI is moderate) and (Mallampati is high) and (NC is moderate) then (Severity is moderate) (1)
5. If (SpO is moderate) and (BMI is moderate) and (NC is moderate) then (Severity is moderate) (1)
6. If (SpO is small) and (BMI is moderate) and (Mallampati is high) and (NC is moderate) then (Severity is moderate) (1)
7. If (SpO is small) and (BMI is moderate) and (Mallampati is mild) and (NC is moderate) then (Severity is moderate) (1)
8. If (SpO is moderate) and (BMI is high) and (Mallampati is mild) and (NC is high) then (Severity is moderate) (1)
9. If (SpO is moderate) and (BMI is high) and (Mallampati is high) then (Severity is moderate) (1)
10. If (SpO is high) and (BMI is moderate) and (Mallampati is moderate) and (NC is moderate) then (Severity is mild) (1)
11. If (SpO is moderate) and (BMI is moderate) and (Mallampati is moderate) and (NC is moderate) then (Severity is mild) (1)
12. If (SpO is high) and (BMI is high) and (Mallampati is high) and (NC is high) then (Severity is severe) (1)
13. If (SpO is moderate) and (BMI is moderate) and (Mallampati is high) and (NC is high) then (Severity is moderate) (1)
14. If (SpO is high) and (BMI is moderate) and (Mallampati is mild) and (NC is high) then (Severity is moderate) (1)
15. If (SpO is high) and (BMI is high) and (Mallampati is high) and (NC is high) then (Severity is moderate) (1)
16. If (SpO is high) and (BMI is high) and (NC is moderate) then (Severity is mild) (1)

Fig. 8. Rules of our FES. Numbers in the parenthesis refer the weight of that rule. Here, all rules are equally weighted.

Inference

Inference is a process of finding a fuzzy consequent based upon inputs and rules. Each rule gives a result for given inputs and all of these results are aggregated to obtain a combined result. We used Mamdani method for inference. Figure 9 shows graphically how the method works.

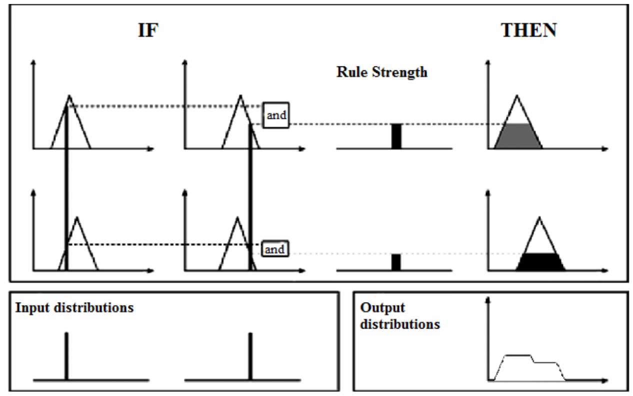

Fig. 9. Graphical representation of Mamdani method [38]. Columns of first box correspond to fuzzy sets and rows correspond to rules. Each input fires a rule to some extent and minimum strength determines the output. Aggregated output, which is the final result, are obtained by combining maximum part of individual rule outputs. For that reason, Mamdani method is also called as max-min method.

Defuzzification

The former step gives a fuzzy output; however, in practice a single result is needed. Defuzzification is the step of converting fuzzy result to a crisp one. We used centroid method to find final output. Calculation of centroid is:

$$z^* = \frac{\int z\mu_B(z)dz}{\int \mu_B(z)dz}, \mu_B \qquad \textbf{(1)}$$

μ_B is the degree of membership of z over fuzzy set B.

V. RESULTS AND DISCUSSION

Results for First Patient Group

Table II shows both the data of the first group (design) and the AHI predictions for each of them. We correctly classified 11 of 14 patients according to disease severity and correlation coefficient between actual AHI of the patients and our prediction is 0.61. This low correlation results from some inconsistencies between actual AHI and the values of data for patients 5, 11, 12, 13. Therefore, we got opinions of domain experts to illuminate the cause of these differences. They explained that obstructions in soft palate, oropharynx and epiglottis cause these differences. Thus, we excluded these patients since we have no appropriate data to add mentioned obstructions to the design.

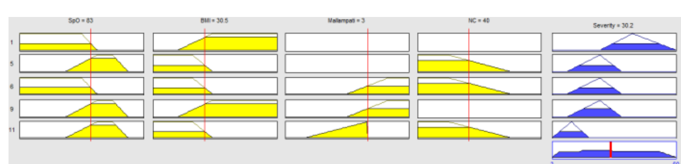

Fig. 10. Fired rules for patient 14. Each row corresponds to the rules (1., 5., 6., 9.,11.) and columns correspond to inputs and the output. The graph in right bottom shows the defuzzification result. Here BMI and tonsil size are more influential than other factors on severity result.

After these exclusions, classification accuracy rises 100%, and correlation coefficient becomes 0.89. Figure 10 shows the fired rules which determine the severity for patient 14

Table II. Patient data and predictions.

Pat.	min SpO_2(%)	BMI (kg/m2)	Mall. Score	NC (cm)	AHI	Pre.
1	82	41.6	4	45	27.1	34.3
2	87	26.4	3	36	13	19.0
3	91	27.3	3	37	11.4	17.9
4	75,3	32.08	2	39	71.2	41.7
5	81	32.8	4	43	19.8	23.3
6	90	24.5	3	40	19.5	18.3
7	79	31.6	2	45	40.4	41.7
8	88,4	27.6	3	38	21.5	17.9
9	81	40.6	3	46	62	42.3
10	85	28.8	1	42	21.5	19.9
11	88,4	35.6	2	43	20	33.0
12	82	38	4	41	10.1	24.7
13	60	38.1	3	45	22.1	35.1
14	83	30.5	3	40	33	27.8

Test Results

Prediction results for test step are shown in Table III. Classification accuracy is 90% and value of correlation coefficient is 0.58. Inconsistency problem here, which is in patient 5, is also available. After leaving this patient out, accuracy and correlation coefficient become 100% and 0.82.

Table III. Predictions for test data.

Pat.	min SpO2(%)	BMI (kg/m2)	Mall. Score	NC (cm)	AHI	Pred.
1	81	28	2	37	23.7	27,8
2	75	29	4	37	25	32,8
3	87	24.5	3	37	13.8	18,4
4	68	28	3	40	40.9	35,1
5	72	41	2	41	15	41,7
6	78	26	4	44	52	38,4
7	86	27	3	39	15.4	18,8
8	75	31.3	4	45	32.7	41,7
9	73	28	4	42	31.2	37,9
10	82.64	22.6	2	40	19	21,6

When the tables are examined, some extreme AHI values such as 71.2, 62 are seen and our predictions do not close these numbers. Actually, what we try to do here is not to exactly find the AHI values; instead, our focus is to correctly classify the patient with consistent results. Also, we aimed to show that standard AHI intervals for severity classification may not be so crisp, as it is now. For instance, AHI value of patient 1 in train set is 27.1 which mean the patient has moderate OSAHS. However, our prediction, 34.3, indicates that the patient has more severe OSAHS than moderate since 34.3 has also a membership degree in “severe” fuzzy set. Support for this prediction comes from intrinsic challenges of PSG. In order to obtain accurate AHI, these minimal conditions have to be provided: sound proof and climatized room that can be kept in complete darkness, a comfortable bed and the technical installations for recording the biological signals, avoiding the patient from the use of sleeping pills or narcotics several days before the study and from strenuous physical exercise on the day of the study, and not to drink coffee, black tea or alcoholic beverages [39]. Insufficiency in one of these conditions may result in misleading AHI result by reducing sleep quality. Moreover, OSAHS may be result from sleeping in supine position and it is shown that PSG may overestimate the severity of OSAHS in some patients with positional OSAHS [40].

VI. Conclusions

In this study, we determined severity degree of OSAHS by means of min SpO_2, BMI, Mallampati Score, NC and evaluated the predicted results with AHI. Results show that fuzzy logic can be successfully applied for that problem. Although, we obtained the min SpO_2 data from PSG, it is possible to get this data by nocturnal pulse oximetry which is readily available, relatively inexpensive and can be easily done at home. Our study shows a possibility of simpler alternative to PSG and proposes fuzziness in standard AHI intervals as different point of view. Powerful visualization ability of Matlab also contributes our study. For example, Figure 10 helps to see which risk factor predominates on the severity condition and this may direct the decision about treatment. In a later study, we are planning to test our model on more patient data which no PSG is used for any part of data collection process. Also, we aim to integrate our FES with hospital information system by which a risk evaluation can be done automatically using available patient information without requiring separate data collection. This system will be able to warn physician to further investigate OSAHS risk as well as affecting his/her medical decision about the treatment of current disease of the patients.

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NON CLASSICALITY IN MIND

D. Turkpence

Abstract**—** Understanding the mechanisms of human decision making is of significant importance to the cognitive science. Today's motivation on artificial intelligence and machine learning has been focused on more humanoid machines. Classical machine learning algorithms are based on classical logic and probability. However, empirical evidence shows that human decision behavior reveals some non-classical aspects such as context effects, order effects or ambiguity aversion. Electroencephalography (EEG) is a well-known way to obtain and interpret the brain signals for diverse goals. This study presents standard EEG methods to obtain the data, then some methods will be briefly surveyed analyzing non-classical effects by using EEG data.

Keywords**—** *EEG methods, Quantum non-locality, Cognitive systems*

I. INTRODUCTION

THE underlying motivation for obtaining brain signals as a result of neural activity has been the need for diagnosis and treatment of brain dysfunctions, disorders and illnesses. The first extracted brain data was taken in 1875 by Richard Caton in Liverpool by a Galvanometer over the scalp of a subject with two electrodes. This was used to explain epileptic attacks by the observed electrical anomalies of the signals [1].

The existence of the brain EEG signals discovered Hans Berger by more powerful double Galvanometer [2, 3]. Berger declared the alpha rhythm as the main ingredient of EEG signals. He also discovered some relations between EEG signal variations and mental activities in his later studies.

Kornmüller signed out the importance of the positioning of electrodes and the multi-channel recordings [4]. In 1947 the American EEG society was founded and the first congress was held in London. The EEG studies are still in progress with the focus of clinical and data processing studies. Today, EEG recordings have been known as invasive and non-invasive recording integrated with computer systems. The obtained data is subjected to the advanced tools of many signal processing methods. EEG signals are obtained by secondary electrical fields generated by electric current flows between synaptic junctions of neural cells. Human head attenuates the EEG signals more than two orders of magnitude and the obtained EEG data consist environmental and internal noise.

Today, on one hand we witness the rapid development of artificial intelligence and machine learning, on the other hand we continue the effort on understanding the brain and human behavior. In this respect, the EEG data could provide an important information content as an empirical data.

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There is a huge literature on the human behavior violating the basic axioms of classical probability theory or depicting some non-classical effects [5, 6]. The well-known formulation for non-classicality or non-locality is Bell inequalities introduced by John Bell [7]. John Bell demonstrated that violations of Bell inequalities implies the non-classical behavior of quantum systems. A variant of these inequalities in the time domain are called Legget Garg inequalities proposed by Legget-Garg in 1985 [8]. These inequalities are sometimes called temporal Bell inequalities implies the non-locality in time.

In this article, we discuss brain rhythms and EEG signals. Then we review some studies analyzing the non-classicality of brain rhythms by investigating EEG data in terms of LG inequalities.

II. BRAIN RHYTMS

Brain defects could be diagnosed by careful analysis of EEG recordings. In our case, we will be interested in healthy subjects. There are five main distinguishable brain sourced waves change with wakefulness and sleep. The major frequency bands are alpha, theta, beta, delta and gamma waves.

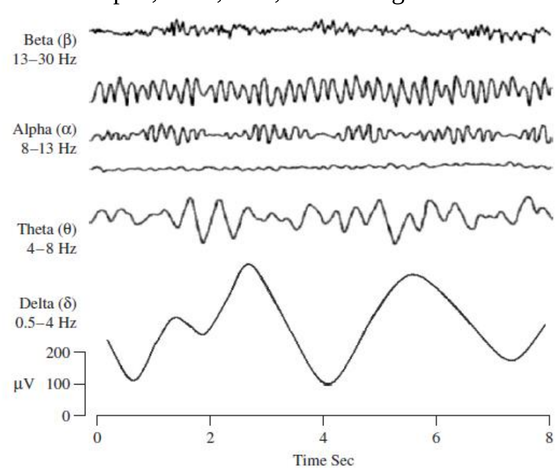

Fig.1. Typical brain rhythms, with descending frequencies. The delta wave is observed in infants or sleeping adults, the alpha wave is detected when there is no attention, and the beta wave shows up frontally and laterally.

Delta waves has the lowest frequency range which lies between 0.5- 4 Hz. These waves are associated with deep sleep and could be easily confused by artefact signals from the muscles. Theta waves has the have the frequency range 4-7.5 Hz and represent the consciousness shifts towards relaxation and unconsciousness. These waves would also be associated with mediation. Variation in the theta wave rhythms has been the subject of emotional studies [9]. Next band is the alpha waves lying within 8-13 Hz thought of representing awareness with low concentration. They have generally smooth or sinusoidal shapes and sharp shapes in rare situations. It's accepted that alpha waves show up in the posterior side of the head and cover a wide range of brain activity. In most cases, alpha waves are produced during the eyes closed but reduced during the eyes opened or a sound heard. The physiological impact of alpha waves is still under research [10].

Beta waves constitutes the range of 14-26 Hz which are known as usual waking rhythm. These waves are associated with active thinking, high-level attention. A beta wave frequency level could be enhanced during a panic case. The brain waves with frequency above 30 Hz correspond to gamma waves. These waves generally lies within 30-45 Hz and their detection is rare. Their presence indicates certain brain diseases. Fig.1 demonstrates the aforementioned brain rhythms with corresponding frequency ranges.

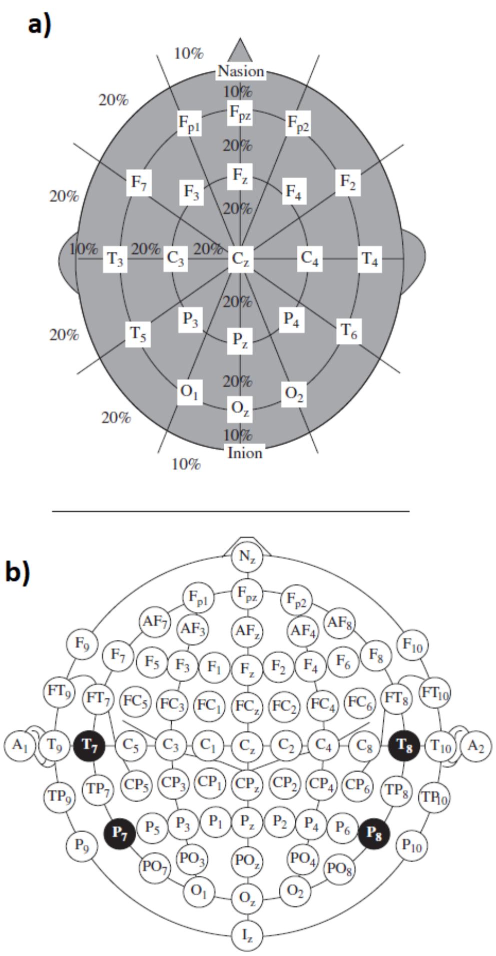

Fig. 2. Typical brain rhythms, with descending frequencies. The delta wave is observed in infants or sleeping adults, the alpha wave is detected when there is no attention, and the beta wave shows up frontally and laterally [11].

Effective signal bandwidth is restricted to around 100 Hz and a 200 Hz sampling frequency is generally sufficient for sampling EEG signals. The international federation of societies for EEG has recommended the conventional electrode setting for 21 electrodes. As in Fig.2 [11] the even electrodes are on the right side and the odd ones are on the left. In this system, more number of electrodes can be placed in between the above electrodes with equidistance. As in Fig.2b, C_1 is placed between C_3 and C_z on the left side.

In some cases, only single channel EEG recording may be sufficient. For example, C_3 or C_4 electrodes have convenient placements for the movements of the right and the left fingers respectively. In some other applications such as human-computer interfacing, a few numbers of electrodes might be selected from the conventional setting system.

III. BISTABLE PERCEPTION

It's been proposed that the characteristics of quantum theory can be used for exploring the dynamics of the systems outside physics [12]. One example is a bistable perception of human which has been an interesting topic since the report of Necker [13]. As depicted in Fig. 3, only one perspective over two possible perspectives perceived at a time.

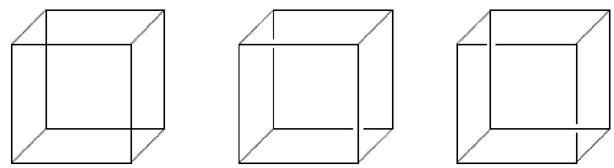

Fig. 3. Necker cube (leftmost) and the corresponding two possible representations.

Under continuous time evaluation the perspectives of ambiguous figures switches in an uncontrollable manner. There are various studies reported extracting EEG data taken by ambiguous figures stimuli [14, 15].

Generally, experiments held by middle aged subjects pressing a button during the percept reversal. Atmanspacher modelled this bistable perception phenomena by a quantum model violating LG inequalities [16]. The proposal based on the Necker-Zeno model reported in 1977 by Misra&Sudarhan [17]. According to Atmanspacher proposal, mental states described by described by a two state quantum system. The random switches between the two states of the system describes by a unitary operator$U(t)$. They also consider a realistic time scale in the order of ms in terms of mental states. Piantoni *et.al.* demonstrated a bistable perception example highlighting the alpha power by using EEG record [18]. According to the results, high alpha power associated with the long and stable perceptual representations. On the other hand, during the reversal of perceptions low alpha power recorded. It's pointed that alpha rhythm power can predict the unstable occurrence of perception with the same stimuli.

IV. CONCLUSIONS

In this review, EEG studies and unstable perceptual effects simply surveyed. Processing EEG data has been developed as a mature field of research with more than 60 years' experience. Now the EEG data has been the subject of an intense research beside the diseases and diagnosis. Particularly by the idea to use the EEG data in order to understand human behavior, the field remains accessible for psychologists trying to understand non-classical behaviors and ambiguities of humans. Here, we conclude that alpha power would be a fair point of study particularly to understand the bistable perception or similar non-classical decision-making mechanisms.

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BIOGRAPHIES

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ANALYSIS OF EPILEPTIC SIGNALS BASED ON DISCRETE HARTLEY TRANSFORM AND DISCRETE FOURIER TRANSFORM

A. Horiushkina and Y. Breslavets

Abstract— In this paper, the proposed approach to the problems of assessing the rhythms of the brain develops an analysis is made of the existing features of processing neurological signals. For the analysis of epileptic discharges, which are the focus of work, it is proposed to use orthogonal transformations. This was done on the basis of a reasoned model of epileptic discharges as a class of broadband pulse signals. The analysis of the main features of the discrete Fourier and Hartley transforms is presented as the main methods of signal processing in the case of epileptic seizures is carried out. The results of the analysis of the real, containing a fragment of the epileptic discharge of the EEG record obtained on the basis of the proposed approach are presented.

Keywords— *EEG signals, Dıscrete Fourier transform, Dıscrete Hartley transform, processing, simulation*

I. INTRODUCTION

THE problem of epilepsy is one of the most common neurological chronic diseases that affects a large number of people around the world. Statistics show that today the risks of sudden epilepsy are increase. Such cases often lead to premature death. Epilepsy is a sudden periodic disruption in the brain, associated with the hyper synchronization of electrical activity of neurons. A distinctive feature of epilepsy are repeated seizures-discharges. Attacks occur accidentally, disrupting the normal functioning of the brain in an unpredictable manner. Figure 1 shows an example of EEC record with an explicitly distinguishable [1-7]. Currently, the main means of neuroimaging used to detect epileptic discharges are EEG (electroencephalography), MEG (magnetic-encephalography), and more recently also MRI (magnetic resonance imaging).

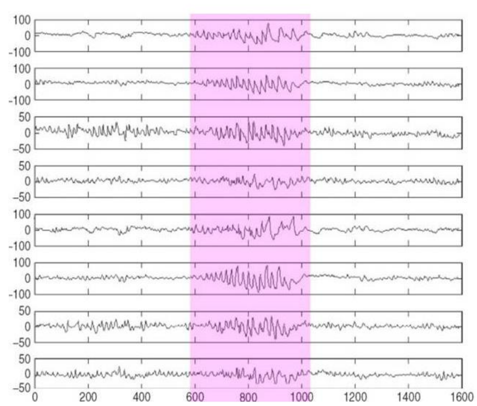

Fig. 1 EEC record with an explicitly distinguishable.

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However, the number of MRI machines is limited, they are expensive and scanning with them takes a long time. From MEG, on the other hand, due to sensitivity to the mobility of the patient, to other artifacts, it is difficult to obtain clear data, especially in moderate and severe cases. That is why, the EEG remains is a most useful and cost-effective method for studying epilepsy.

Researching's show, there are methods of processing signals that allow quickly and accurately process and transmit incoming information to the devices. Such representatives are the Dıscrete Fourier transform and the Dıscrete Hartley transform. Analysis of the literature shows that good results can be obtained with the aid of orthogonal transformations. Therefore, the issue of quality, informative signal processing in the case of epileptic seizures is topical [1-13].

II. METHODS OF PROCESSING EEG SIGNALS

In this article, for processing neurological signals, orthogonal transformations are taken as a basis. We will analyse the main transformations, namely, the Dıscrete Fourier transform and the Hartley discrete transformation [6].

A) THE DISCRETE FOURIER TRANSFORM (FFT) is one of the transforms widely used in digital signal processing algorithms, as well as in other areas related to the analysis of frequencies in a discrete signal. The discrete Fourier transform requires a discrete function as an input. Such functions are often created by sampling, namely sampling values from continuous functions.

Providing the analyse of some properties of the discrete Fourier transform

1. Linearity. If we take some linear combination of functions, then the Fourier transform of this combination will be the same linear combination of the Fourier images of these functions. This property allows you to reduce complex functions and their Fourier images to simpler ones.

2. Independence of the amplitude spectrum from the time shift of the signal. With moving of the function to the left or right along the x axis, only its phase spectrum will change.

3. Extension of the original function along the time axis (x) proportionally compresses its Fourier image on the frequency scale (w). The signal spectrum of finite duration is always infinitely wide and vice versa, the spectrum of finite width always corresponds to a signal of unlimited duration.

4. Convolution of functions which allow to reduce the convolution of functions to the pointwise multiplication of their Fourier transforms and vice versa - pointwise multiplication of functions to the convolution of their Fourier transforms.

5. Symmetry. In particular, it follows from this property that in the Fourier transform of a real-valued function, the amplitude spectrum is always an even function, and the phase spectrum is odd.

6."Energy" of the signal. It is meaningful only for signals of finite duration, the energy of which is finite, and indicates that the spectrum of such signals at infinity rapidly approaches zero. It is by virtue of this that properties on the spectra graphs are usually represented only by the "main" part of the signal, which carries the lion's share of energy - the rest of the graph simply tends to zero.

It is proved that if some periodic function with period 2T on interval [-*T*, *T*] satisfies the *Dirichlet* conditions (is continuous and has a finite number of extrema and points of discontinuity of the first kind), then it can be being represented as the sum of a Fourier series (expanded in a Fourier series):

$$f(x) = a_0 + \sum_{n=1}^{\infty} (a_n \cos\frac{n\pi x}{T} + b_n \sin\frac{n\pi x}{T}) \qquad (1)$$

To determine the coefficients of the Fourier series, the following formulas:

$$a_n = \frac{1}{T}\int_{-T}^{T} f(x)\cos\frac{n\pi x}{T}dx$$
$$b_n = \frac{1}{T}\int_{-T}^{T} f(x) sin\frac{n\pi x}{T}dx \qquad (2)$$

If the decomposable function is even ($f(-x) = f(x)$), then the Fourier series consists only of cosines, that is, all the coefficients of the signs are 0. If the decomposable function is odd ($f(-x) = -f(x)$), then the Fourier series consists only of sines, that is, all the coefficients of the cosines are 0. In general, the coefficients of sines and cosines are not equal to 0. Thus, any periodic function satisfying the *Dirichlet* conditions, can be expanded in a Fourier series, thereby representing it in the form of a sum of sines and cosines. The spectrum of a discrete periodic signal can be calculated at help of a discrete Fourier transform (DFT) [8].

To determine the amplitudes and phases of the frequency components of the signal, in discrete Fourier transform uses the basic functions of the sine and cosine. The spectrum of frequencies in a discrete Fourier transform is determined from amplitudes of sines and cosines, with repetition frequencies in the studied.

Discrete Fourier transform descrıbıng by formula:

$$X_k = \frac{1}{N}\sum_{i=0}^{N-1} x_n e^{-j\frac{2\pi ki}{N}} = \\ = \frac{1}{N}\sum_{i=0}^{N-1} x_n \left[\cos\frac{2\pi ki}{N} - j\sin\frac{2\pi ki}{N}\right] \qquad (3)$$

The sample is from 0 to N / 2 times, where N - is the number of sample elements. The Fourier transform decomposes a sampled signal from N counts on N / 2 + 1 sine and N / 2 + 1 cosine components.

B) THE DISCRETE HARTLEY TRANSFORM (DHT) is a kind of orthogonal trigonometric transformation. In many cases it can serve as a substitute for a transformed into a sequence *N* of real numbers H_0, H_1, ..., H_{N-1} by means of the Hartley transform according to the formula:

$$H_k = \frac{1}{N}\sum_{n=0}^{N-1} h_n cas\left(\frac{2\pi}{N}nk\right), k = 0,...,N-1 \qquad (4)$$

From the figures 2, 3 can be seen that in the DFT there is no block of transition of the real part to the complex the area. This reduces the time spent on this transformation. For example, with the length of the input sequence of 10 counts. We have 10 operations of multiplication each operation is realistic for 10 cycles. Each cycle lasts for 2 seconds. For a given sequence length, we have a decrease in the time of the completed conversion for 2 sec. The time spent on processing DFT and on DFT differ.

The processing time of the DPC is 2 seconds faster than the DFT. As shown by the conducted studies with an increase in the volume of data, the time spent on data processing is also reduced in the case of DHT. Mechanism of epilepsy and the way of researching by methods of spectrum analysing.

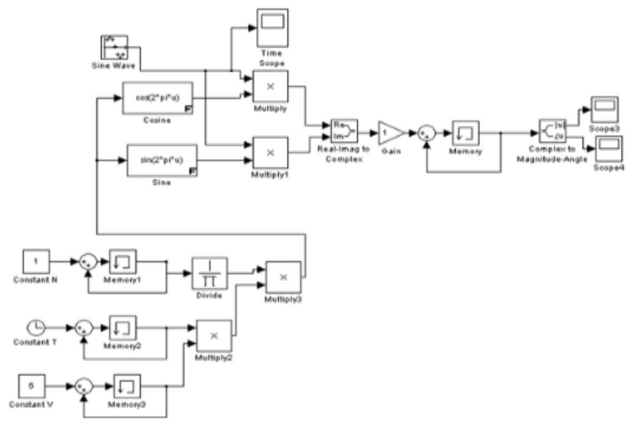

Fig. 2 – Structural scheme of discrete Fourier transform

In the Hartley definition for the transformation φ (ω), the coefficient $1/\sqrt{2\pi}$ was explicitly included to obtain a symmetric expression. Without this coefficient, then both integrals cannot simultaneously be correct. However, it should be considered inadvisable to maintain a pair of such specific coefficients, especially when performing numerical calculations. Was considered to change the function $\sqrt{2\pi}$ S (ω) instead of *S* (ω). As a result, the coefficient $1/\sqrt{2\pi}$ disappears in the definition of the direct Fourier transform, but in the formula of the inverse Fourier transform, the coefficient 1/2π became appears. Thus, intentionally sacrifice the symmetry of formulas. It is fair to say that this is an additional load for the memory, since it is necessary to remember which of the formulas contains the value 2π. One way to remember is that the coefficient 1 / 2π stands before the integral in which the differential d*ω* appears, which means the presence a quantity of the form ω/ 2π, that is, of the cyclic frequency *f* [8].

Epilepsy is a serious and fairly widespread disease of the brain.

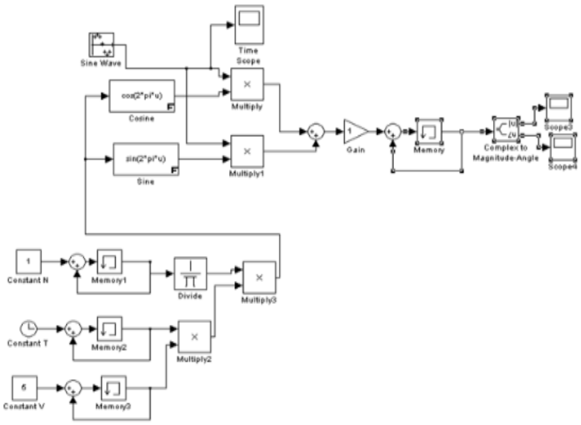

Fig. 3. Structural scheme of discrete Hartley transform

Typically, a qualitative description of the electrographic picture of discharges is given, features of the distribution of pathological activity along the areas of the cortex and other brain structures are determined, and some average quantitative estimates of epileptic seizures (mean duration of discharges, percent of time occupied by discharges and some others) are made. However, for differential diagnosis of different types of epilepsy, it is also useful to quantify the frequency-temporal organization of discharges and its dynamics for different types of epilepsy. Epilepsy is a chronic disease of the brain, characterized by repeated unprovoked attacks of motor, sensitive, vegetative, mental or psychic functions that occur due to excessive neuronal discharges [7-14].

One of the possible mechanisms for the development of epileptic form activity is due to the fact that cells generate bursts of impulses as a result of the potentiation of glutamatergic synaptic transmission and changes in calcium channel activity. The very synchronization of discharges, as is well known, is also found in normal, for example, in the generation of EEG rhythms.

Epilepsy is a chronic brain disorder characterized by repeated unprovoked attacks of motor, sensory, autonomic, mental or mental functions that occur due to excessive neuronal discharges. A common clinical sign in various forms of epilepsy is the occurrence in the brain of high-amplitude electrical discharges that are the result of simultaneous excitation of a large the number of neurons. Typically, a qualitative description of the electrographic picture of discharges is given, features of the distribution of pathological activity along the areas of the cortex and other brain structures are determined, and some average quantitative estimates of epileptic seizures (mean duration of discharges, percent of time occupied by discharges and some others) are made. However, for differential diagnosis of different types of epilepsy, it is also useful to quantify the frequency-temporal organization of discharges and its dynamics for different types of epilepsy [1-5].

One of the possible mechanisms for the development of epileptic form activity is due to the fact that cells generate bursts of impulses as a result of the potentiation of glutamatergic synaptic transmission and changes in calcium channel activity. The very synchronization of discharges is the norm, as in the generation of EEG rhythms.

There are many models for the study of epilepsy and all of them can be divided into several types - pharmacological, where a single administration of the substance provokes epileptic seizures; chemical handling, electric kindling, in which a chemical agent is used instead of a chemical agent electrostimulation by implanted electrodes; and various genetic models with some age limitations [9].

During the investigation and processing of the signal, a lot of useful information can be obtained from an analysis of its frequency characteristics. The Fourier transform (spectral analysis) represents a signal specified in the time domain in the form of an expansion in orthogonal basis functions (sines and cosines), thus allocating frequency components.

The initial data were taken when measuring the bioelectrical activity of the brain. The EEG was recorded in the laboratory. The data of the EEG signals were obtained and used in this work.

Spectral analysis is already classical methods of EEG processing. Fourier analysis allows us to judge the presence in this wave process of certain EEG rhythms and their individual expression.

Simulation of the source signals using orthogonal transformations.

For further research, signals were used that simulate the state of epileptic seizures and are also included in the mathematical simulacrum. The graphs of the original signal of the Hartley and Fourier transformations are mapped appropriately

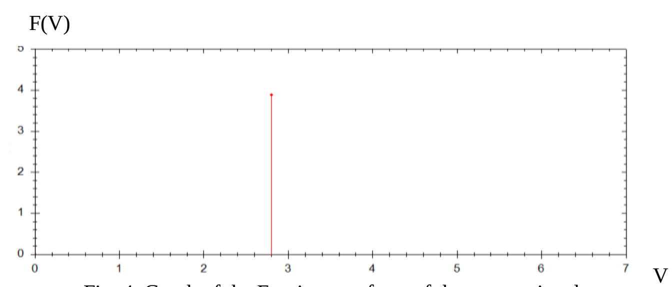

Fig. 4. Graph of the Fourier transform of the source signal

The results of the simulation were carried out in the Matlab system as well as with the help of the generated code of the C ++ program.

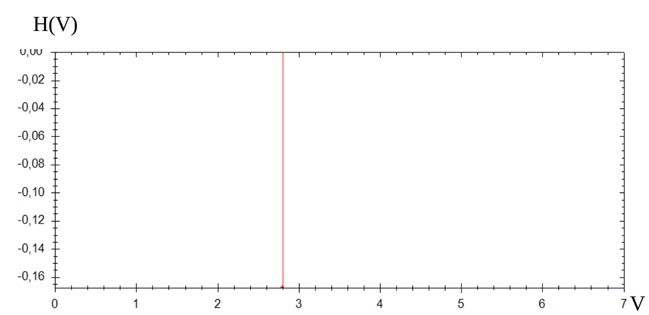

Fig. 5. Graph of the Dıscrete Hartley transform of the source signal

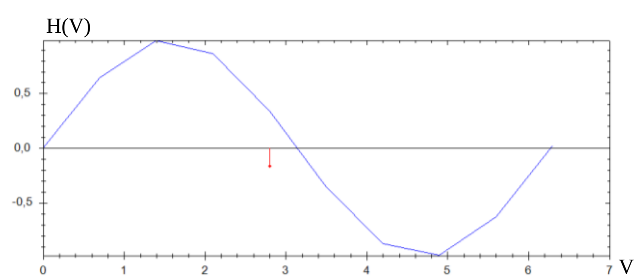

Fig. 6. Graph of the Dıscrete Hartley transform and the source signal

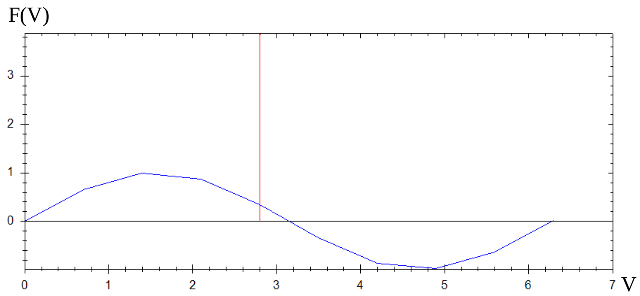

Fig. 7. Graph of the Discrete Fourier transform and source signal

The DFT vector has a physical meaning, namely, if the vector is a DFT signal, then the DFT decomposes it by frequency. Transformation Hartley does not have such a clear interpretation. Therefore, if the original data is valid, then the DHT may be larger effective than FFT. It is sometimes possible to transfer the DHT in the DFT. Avoid, and an example of such an approach is considered when multiplying long numbers [11-12].

III. CONCLUSIONS

At present, it has been established that epilepsy is not a single disease with various seizures, and is divided into separate forms – epileptic syndromes characterized by a stable relationship clinical, electrical and anatomical criterion, reaction on antiepileptic therapy and prognosis. Accordingly, the nature and severity of cognitive impairment varies with different forms of epilepsy. The aim of this work was a general study epileptic signs, mechanisms of their occurrence, the analysis of similar signals and spectral methods of their processing. The results of the research showed that discrete orthogonal transformations have good opportunities for qualitative processing of epileptic signals. In particular, two main transformations were compared, namely, the discrete Fourier transform and its analogue the discrete Hartley transformation.

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ROBOTIC ARM CONTROL USING THE BRAIN WAVES

A. Karakoc, D. Dogan, and T.C. Akinci

***Abstract*—** Although the human brain has not solved the mystery in full, significant progress has been made as a result of scientific studies on the brain. Through the electrodes connected to the human brain, the EEG signs of our thoughts can give information about the current intellectual and physical state of the human. With the signals from the brain through the EEG biosensors, we can measure the motivation level of our brain. Depending on our state of thought or motivation, changing signs can be used to control a system. This study consists of four stages. Robotic-hand design was made in the first stage. Plastic parts in robotic-hand design are drawn by CAD (Solid) program and produced by 3D printer. In the second stage, the servomotor and the necessary mechanisms are placed into the plastic model and the joints are moved by the motors that pull the lines of the line for the correct movement of the fingers. The third stage is the software phase that will control the movement of the servo-motors in the bionic hand. Software codes have been created for the Arduino card to control the system. In the fourth and final stage, the study was carried out by practicing on how the individual would be motivated by the use of the bionic hand sensor with the brain waves sensor.

***Keywords*—** *EEG sensors, Brain Wave control, Robotic Arm.*

I. INTRODUCTION

AS is known, one of the most important diseases limiting human movements is paralysis and loss of limb. Genetic reasons, accidental or various diseases may have caused these losses. These losses can cause neurological disorders. These patients come to this level, especially as a result of some scans. These patients may not be able to perform their own care because of their illness or they may experience communication difficulties. The use of brain signals can help these patients communicate with other people. Systems that detect EEG signals and convert them to control signals can be designed. These systems transform people's thoughts into signs that control mechanisms by means of software [1].

Thanks to the latest technological advances, EEG sensors and other intelligent sensor groups have been developed, which can be controlled by the patient's brain commands. *Beyrouthy* et al created a hand model with 3D printer by friends. Servomotors provide the movements of this prosthetic model. This model shows the ability to make movements that are suitable for many scenarios. These scenarios are selected from real human movements. Computer algorithms generate all these movements.

Experimental results show that; EEG thought / motivation studies are promising and alternative for solutions requiring surgical interventions [2].

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Researchers have recently proposed new scientific methods to restore the function of lost abilities for patients with neuro-motor disorder. One of these methods is to provide a new non-muscle communication and control channel to the brain, ie a direct Brain-Machine Interface (BMI). A study by Howida et al. presents a BMI system using brain EEG signals associated with movement of the arm to control a robotic arm [3]. In the literature, many studies have been performed using brain waves (sensors / vibrations) [4-7]. The CBI (Brain Computer Interface) makes it possible for people to use a computer, an electromechanical arm, or a variety of neuro-prostheses without using the motor nerve systems. In particular, these systems are of paramount importance to improve the quality of life of patients with paralysis and Amyotrophic Lateral Sclerosis (ALS). The brain computer interface is a new technology that allows people to communicate with electronic devices such as computers, where they use brain waves called electroencephalogram (EEG).

The aim of this study is to facilitate the lives of patients who cannot use their fingers or their hands with the EEG biosensor. In addition, patients with paralysis or ALS should develop a model that is closest to the human hand so that they can live their lives better, and that this model is used by the patient with an EEG sensor. Moreover, because this model is an electromechanical model, it may be possible to evaluate it as an engineering design and application.

II. BRAIN, STRUCTURE AND FUNCTIONING

The brain is a complex organ that forms part of our Central Nervous System (CNS) and is the largest part of our encephalon. It is located in the anterior and upper part of the skull cavity and is present in all vertebrates. Inside the brain skull is located in a transparent fluid called spinal fluid, which maintains it both physically and immunologically [8]. The function of the brain as part of the Central Nervous System is to regulate the majority of body and mind functions. Respiration, heart rate regulation, thinking, talking, etc. all life functions are the task of the CNS.

Although the brain is composed of three main parts: the forebrain, midbrain and posterior brain, the brain has a much more complex structure [9]. This complex structure consists of various regions. These regions undertake different tasks. Seeing, hearing, tasting, motion controls, perception and speech are controlled from different parts of the brain [9].

The cerebellum is located at the back of our heads. The cerebellum helps keep our body in balance. In addition, the muscles are compatible with each other. The most basic task of the cerebellum is to provide balance and to evaluate the warnings from the eye [9].

The spinal cord is the posterior brain portion located between the spinal cord and the pons. The spinal cord on the dandruff, just like in the cerebellum and spinal cord substances are available. The motor nerves in the brain are also distributed diagonally across the spinal cord. The most important tasks of spinal cord bulb; Digestive, respiratory, circulatory and excretory systems to ensure the operation. In addition, controlling and regulating the blood sugar of the liver controls vital reflexes such as swallowing, sneezing, coughing and vomiting [9].

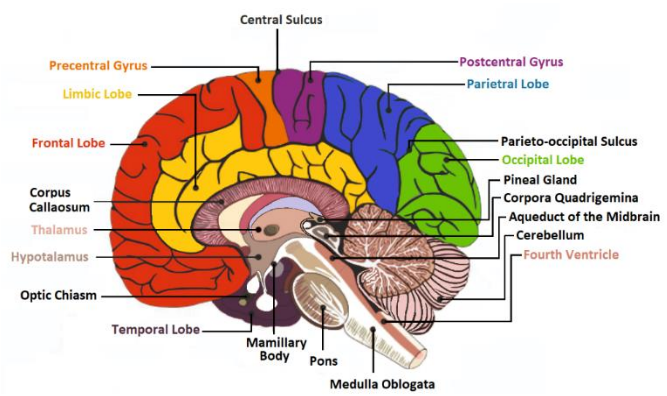

Fig.1 Internal parts of the brain [9].

Brain in humans is one of the most advanced and complex among all animal species. It is not only bigger but also twisted and folded, creating grooves and layers in itself, which gives it a wrinkled appearance. The human brain weighs about 1.5 kilos. The weight of the brain constitutes 2% of the weight of human weight. It has excellent cell management. It has approximately 86 billion nerve cells. The human brain is approximately 1.4-1.5 kilos (3.3 lbs), and its volume is approximately 1130 cc in women and 1260 cc in men. The majority are composed of glial cells and neurons [8].

These nerve cells, *ie*, neurons, are connected to each other by trillions of neural networks (neurons). Neurons are specialized cells that receive, process and transmit information at the intracellular and intracellular levels. This is done through electrochemical signals (neural hills) called action potentials. Neurons consist of three parts: cell body, axons and dendrites. One of the most important cells to perform cellular nervous system functions is Glia Cells. These cells provide structural support to neurons, covering axons with axons for better synaptic transmission. Neuroglia (Glia) Cells, Schwann cells are classified as Oligodendrocytes, Astrocytes, Ependymal cells and Microglia cells [10].

The development of the human brain begins at the embryo stage and ends in youth. Four weeks after falling into the mother's womb, the brain begins to form a neural tube from which the brain stem comes. Then, the process of proliferation, migration and cell decomposition, in which the formation and development of the brain takes place, begins. Neurons are produced in the neural tube and then transported to form important parts of the brain. Finally, they will be separated and specialized according to the function they will have.

III. BRAIN WAVE SENSOR (EEG SENSOR)

Defining and grouping activities in the brain was quite difficult in the past years. However, as a result of studies conducted by Hans Berger, an electroencephalogram was invented. Berger is considered the founder of EEG. Berger also attracted attention by putting different diagnoses on his work. Berger preferred different diagnosis and treatment methods for individuals who had a tumor in his brain. Berger has been successful in using therapies to diagnose the signals he has recorded from the electrodes he has worn on the non-invasive scalp [12].

Electroencephalogram; EEG is the measurement of electrical impulses of neurons. Therefore, it helps to investigate the cognitive activities of human beings. The processing and interpretation of EEG signals by using signal-processing techniques is based on different approach algorithms. EEG-based technology is more preferred in clinical neurology than other radiological imaging methods. EEG-based technology is not only medically limited, but a lot of research is being carried out due to the analysis and interpretation of brain waves.

The brain computer interface (BCI) is one of the communication channels developed to interact between the human brain and the digital environment to control / operate external devices. When designing this interface, it is aimed to increase the living standards of disabled and old people by considering the medical interests. The system aims to control the devices by interpreting the brain wave frequencies in the mind. Many studies have been done for this.

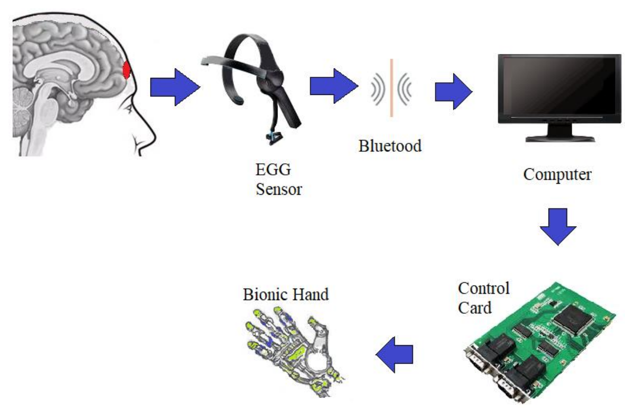

Fig.2. Brain Computer Interface and measurement systems.

Electroencephalogram (EEG) markings are low-amplitude (1-400 μV to top hill) bioelectric signs measured from electrodes on the brain surface or through the person's scalp. Research has revealed that a large amount of neurological information is stored in these signs. In the last 15 years, the examination of EEG signals has been accelerated, with the use of these markers to develop patient treatment methods and to establish a BCI by means of these signals to communicate with electronic devices.

The first observed by Hans Berger is the 8-12 Hz alpha waves. Hans Berger; In this frequency range, fixed waves appeared but disappeared with opened eyes. When the formation of alpha rhythm is examined, it is proved that it is observed clearly in the records taken from the occipital lobe. In order for alpha activity to be achieved, a person must be in a closed, stagnant physiology. Beta rhythm is the activity with a frequency range of 12-38 Hz in the brain. When the person is awake and fit, the brain performs beta release. The amplitude is usually below 30μV. This brain wave has a logical thinking phase and is largely involved in one's daily life. In case of excitement, the frequency of the beta wave increases at the moment of focus. However, when the brain releases beta waves in continuous and high doses, behavior disorders, addictions, nerves and neurosis are experienced.

Delta activity is the electrical activity with the slowest frequency range (0.5-3 Hz) secreted by the brain. The delta wave appears in deep meditation or deep sleep. Theta waves are low oscillatory waves with a frequency of 5-8 Hz. It is just before the person falls asleep. This frequency plays a role in remembering long forgotten information. Gamma waves have a frequency greater than 30 Hz. Gamma waves play an important role in determining the effect of the external world on neural structure. This rhythm state of depression that spread even spent an adult becomes apparent as soon as possible seizures [13-17].

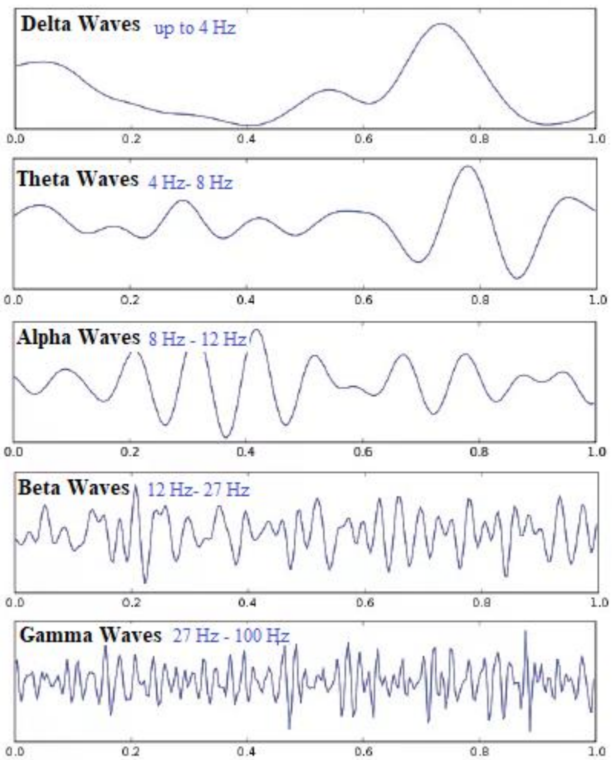

Fig.3. Frequency range of the brain wave [18].

Although the medical standards recommended using the 10-20 electrode system, which is accepted for EEG measurement, recent developments, have shown that high efficiency can be obtained from single channel studies [18]. In this study, EEG biosensor of single channel Neurosky company © was used. This EEG Biosensor can determine the user's mental fatigue, brainwaves, and winks. This product includes a ThinkGear chip that provides the interface between the user's brain and the robot systems. The sensor that contacts the contact and reference points on the forehead and ear, transmits all measured data to the digital form software and applications. The sensor has a sensing range of 10 meters and uses the TGAM1 Bluetooth v2.1 Class 2 module. The frequency used is 12 MHz. The required power is 9-12V. The LPC2148 processor form is used to control these types of devices.

Since the amplitudes of the EEG signals are very low, a variety of noises can be easily confused. It is affected by external factors such as the presence of electrically operated devices in the measurement room, the light being turned on or off, and the presence of devices that can emit electromagnetic waves in the environment. In addition, during the measurement of the person's eye blinking, moving the arm, such as physical activities can be very affected. Various signal processing methods are used in the literature to remove the noise from EEG signals. In this study, signal processing is not mentioned. In the literature, the noise source that is tried to be removed is the noise caused by blink. This noise is particularly confined to the signs in the electrodes located near the eye and in the occipital regions [19, 20].

IV. BIONIC HAND (ROBOTIC ARM) DESIGN

EEG controlled robot arm consists of 61 parts and the required models are printed from 3D printer. Then the joints are connected to the pins. MG-996R type servomotor is used for the movement of the fingers. Arduino provides the control of the motors. Bluetooth 4.0 is used to transfer the signals received from the EEG biosensor to the card.

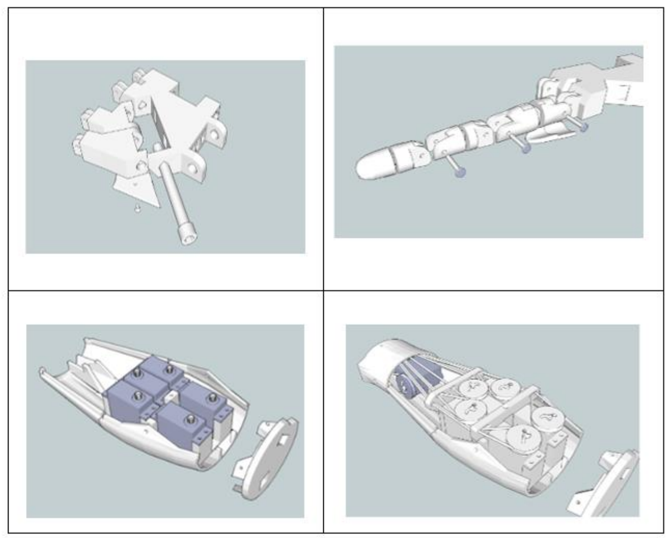

Fig.4. The stages of combining robot arm parts.

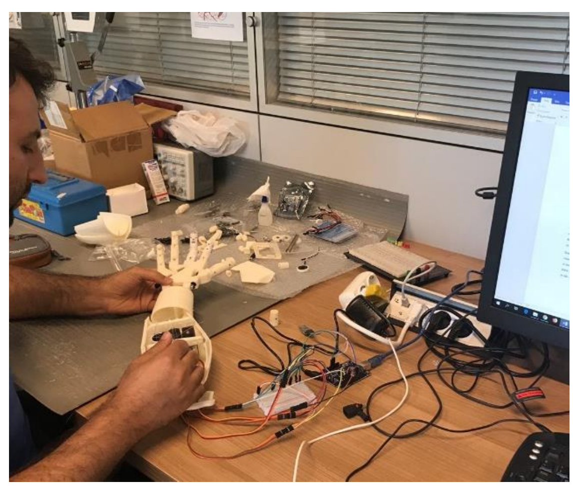

Fig.5. Design and installation of the bionic hand.

To control the bionic hand, the signals from the brainwave sensor are transferred via Bluetooth to the Arduino control card

©. The control card controls the servomotors that control the fingers.

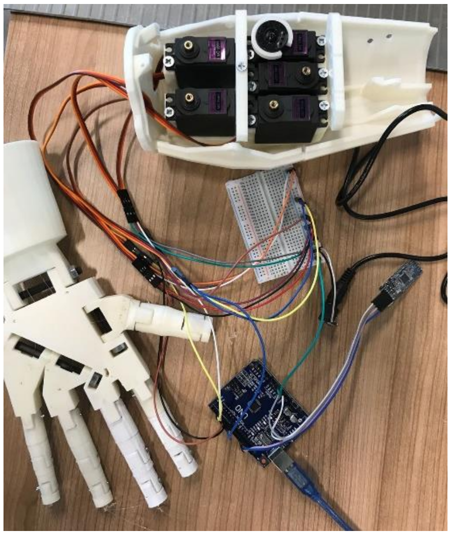

Fig.6. Control of Bionic Hand.

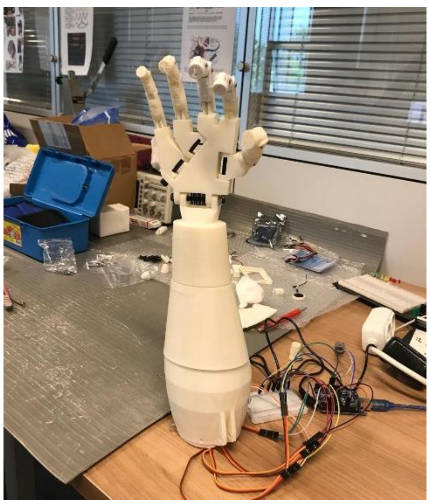

Fig.7. The implementation of the bionic hand..

Figure 4 shows the 3D design of the hand. Figures 5 and 6 show the application of the robotic arm. The procedure is given in Figure 7. Here, modelling and control of the arm is seen.

V. CONCLUSIONS

In this practical study, which was performed for prototyping, it was ensured that the sub-prosthesis was controlled using brain signals. This work can be called bionic-hand or robot arm. In the study, firstly a model close to the human hand was created and modeled with 3D printer, then engines were installed to control this model and control of the motors was made by means of EEG sensor. It consists of working stages, model extraction, control of motors, software and control of the model with EEG brain-sensor. In this application, EEG can open and close the fingers of the model by means of the brainwave sensor. This switch-off has been achieved successfully with the motivation of the person using the EEG sensor.

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COGNITIVE DESIGN METHODS FOR COMPUTER GAMES CONTENT

J. Breslavets, and A. Horiushkina

Abstract**—**A degree in cognitive science provides the opportunity to work in many fields of human and technology. For instance, cognitive science can be used within usability and design, game development, vehicle, road safety, patient safety, technical aids, speech and dictation, technical writer and other forms of processing. Computer game enthusiasts spend many hours in the game, and this intense activity can change the brain and behavior. We consider the studies, which investigate the ability video games to change processes in spatial knowledge in this study. We will outline the initial stages research of the basic mechanisms of training, and also we will consider possible applications this new knowledge. Several experiments have shown that the game of gaming action causes changes in a number of sensory, perceptual and attention that are important for many tasks in spatial cognition**.**

Keywords— *Video game action, Spatial attention, Learning perception, Gender differences, Brain training, Sensory processes, Attentıon processes.*

I. INTRODUCTION

FUNDAMENTAL PROCESSES THAT SUPPORT SPATIAL COGNITION

FOR the most part, early efforts to explore the effects of video games on cognition focused on the relationship between play and performance on paper and pencil tests of spatial cognition. In short, the researchers approached the issue of training from a psychometric point of view. For example, in one of the early studies that studied how video game learning affects spatial cognition, Dorval and Pepin (1986) used the spatial relationship test from the Canadian version (Bennett, Seashore, Weismann, Chevrier, 1960) of the Differential tests of Aptitudes (Bennett, Seashore, & Weismann, 1947) as their measure of spatial proficiency. This test is based on the ability to identify objects hidden on the distraction.

Therefore, the test elements used by Dorval and Pepin most likely have significant requirements for spatial selective attention and spatial working memory. But the authors did not discuss their measure of spatial ability in terms of underlying sensory and perceptual processes. There was no attempt to explore or characterize the mechanisms of spatial learning. Their approach was mostly psychometric - the authors were just wondering if playing a video game would improve the spatial abilities measured by a standard paper and pencil test. Although experiments of this kind are still relevant and often useful, the focus has shifted since the pioneering experiments of green and Bavele (2003), whose studies were the first to explore how playing video games can affect the basic processes of attention. With this groundbreaking work, experimental research has focused on how video games change the basic sensory and perceptual processes that support spatial cognition (e.g. Feng et al., 2007; Green & Bavelier, 2003, 2006b, 2006c, 2007; Li, Polat, Makous, & Bavelier, 2009; Spence et al., 2009)

Video games provide a wide range of sensory, perceptive and cognitive functions. Some games require a high degree of skill when performing relatively basic perceptual and cognitive tasks, while others require higher level cognitive skills, such as the ability to solve complex logical problems. Certain genres offer more advantages for learning than others (Achtman et al., 2008). For example, Feng et al. (2007) demonstrated that participants who played a combat video game for 10 hours achieved significant performance improvements for both attention and spatial tasks, while participants who played a maze game during the same period of time did not achieve any success. Compared to other genres where there have been positive effects of learning the game on spatial skills (e.g. using dynamic puzzles such as Tetris), gaming video games seem to have a unique advantage in improving low-level features such as spatial selective attention (Fen et al., 2007; Green & Bavelier, 2003), spatial perception (Green & Bavelier, 2007), and contrast sensitivity (Li et al., 2009), in addition to more complex spatial skills such as mental rotation (Feng et al., 2007). Since fundamental sensory, perceptual, and cognitive skills serve as building blocks for higher-level cognition, the ability of action games to improve core processes has made them attractive for further experimentation.

II. COGNITIVE APPROACHES TO DESIGN COMPUTER GAMES

The human brain is the most powerful cognitive dynamic system in existence, whıch to assume for an "artificial" dynamic system the cognitive capabilities of the human brain. At the minimum it must have the capacity to perform the following tasks:

- Learning and memory;
- Planning;
- Attention;
- Interaction with the world (environment).

Explanatory Notes on the Perception-Action Cycle:

1. Perception of the Environment involves:
   - Learning and memory;
   - Attention
2. Action performed on the environment involves:
   - planning
   - Control

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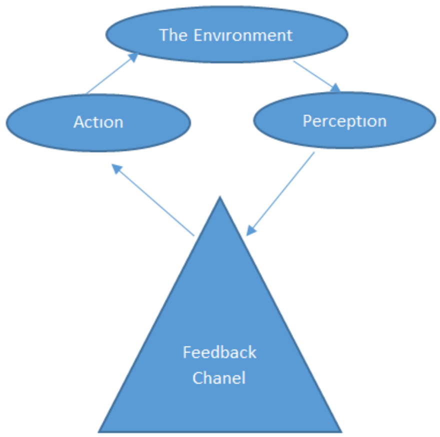

Fig. 1. The Perception-Action Cycle

1) Sensory processes

When light hits the retina, it interacts with approximately 100 million specialized neurons (rods, cones, and other cells), causing some of them to shoot. Numerous calculations are performed at this low level of the visual processing hierarchy, and the results are transmitted to other areas of the brain through approximately 1 million fibers in the optic nerve. Further processing takes place on the way to the visual cortex and along subsequent paths between different areas of the cortex. These paths are not passive one-way streets; lower levels of computation often change in response to inputs from higher centers in the brain (Kellman & Garrigan, 2009; Rolls, 2008; Scolari & Sequences, 2009). The early visual system computes elementary functions such as brightness, edge detection, orientation detection, segmentation, shape perception, three-dimensional perception, motion detection and color processing (Palmer, 1999). These basic operations usually occur without awareness; attention is not necessarily required to ensure their completion. However, recent studies have shown that at least some of these elementary functions are modified by top-down attention-reversal processes (e.g. Gutnisky, Hansen, Iliescu, & Dragoi, 2009; Kastner & Ungerleider, 2000; Polat, 2009).

Advances in computer graphics contributed many games now to have photo-realistic three-dimensional visual environment that is much more realistic than the coarse two-dimensional setting, characteristic of the early games. This allows us to better approach our system of perception, which developed in a three-dimensional environment. As a result, the initial sensory processing of the visual environment in a modern video game takes place with a reasonable facsimile of what we see in the real world. In an FPS game, multiple visual events can occur almost simultaneously, often in widely separated locations in a visual environment. Real images of soldiers, guns, missiles, tanks, planes, ships or any other major types of combat actions can appear and disappear at any time. The first priority of the player is to quickly detect potential threats, and this requires effective scanning of the visual scene. Since the player in the game usually has unlimited freedom of exploration (360 degrees), there is a very large landscape to search for threats. So it's likely that the practice provided by the enhanced FPS game may have some positive benefit for touch processing. However, only recently has evidence been obtained to support this hypothesis. Green and Bavelier (2007) demonstrated improved visual spatial resolution after training with game action, and Li et al. (2009) showed that combat training increases contrast, the fundamental ability required for object recognition and spatial attention. For an additional comment on this rather unexpected result, See Caplovitz and Kastner (2009). Further research may reveal even greater improvement in basic sensory functions because of playing games.

2) Attention processes

The visual system can't handle all the information in the light that reaches the retina. Detailed processing of this continuous data stream would impose a huge and unmanageable computational burden, and in any case such an indiscriminate procedure is not necessary. Most of the raw visual information is not important for survival or for any other relevant purpose and can be ignored. Consequently, the visual system has evolved to be sensitive primarily to changes in position, brightness or other elementary attributes of objects that may be essential for survival. Visual events that are associated with the sudden onset or a change that is especially important, as they say, "attract attention." Attention is immediately directed to the place where the sudden change occurred, for example, when a new object appeared (Yantis & Jonides, 1996). Sudden events are quickly analyzed by the brain using processes that require discrimination, identification, recognition and decision-making, and usually follow eye movements and motor actions. Despite the fact that the mechanism of attenuation capture developed in conditions and circumstances, quite different from today, it remains important. For example, it helps us to be aware of objects that are likely to travel while walking or notice approaching vehicles that may pose a danger when crossing the road. Exciting capture is also very important when playing video games

But attention grabbing is only the first stage - we have to recognize and recognize the objects that have attracted attention while excluding information that is irrelevant to the case. This is visual selective attention. Low-level processes (bottom-up) and processes associated with prior knowledge of objects and their relationships (top-down) are involved; the impact of higher-level cognitive processes is crucial. Working memory, long-term memory and Executive control functions are activated. More than a century of experiments in psychology have shown that many higher-level cognitive processes can be modified through learning (Bourne, Dominowski, & Loftus, 1979); it is therefore reasonable to assume that the practices provided by video game games can also lead to changes in the basic processes of perception and attention as they are affected by higher level cognitive processing. As we have already noted, the processing of visual information is a two-way street. While the perception of lower level provide basic data for cognitive processes of a higher level, these processes are more high level, in turn, affect the systems of perception and attention lower level (Kellman & Garrigan, 2009; Rolls, 2008; Scolari & Serences, 2009).

The player in the game has to detect, identify and track the threats appearing in various locations in a complex and often cluttered visual environment to avoid killing in the game. Thus, practicing in a game can improve the abilities of spatial selective attention, and this improvement of this basic skill can improve performance on other tasks by supporting features that depend on this ability. For example, the practice of recognizing small differences is likely to benefit the perception system as a whole. In a game, the difference between an enemy, a soldier, and a static object far away can be very subtle, especially when the character controlled by the player is moving and the view is constantly changing. To avoid a random attack on a friend and enemy, the player must quickly and accurately identify and identify these small differences while under stress to survive in a dangerous environment. Playing games from most other genres - even dynamic mazes or puzzles that require spatial skills - are unlikely to require such a high degree of skill in spatial selective attention

We can divide our attention into different objects or multiple non-contiguous locations, or we can perform multiple tasks at the same time (Cavanagh & Alvarez, 2005; Kramer & Hahn, 1995). Tracking multiple objects at the same time, visiting multiple locations, or performing two or more tasks at the same time requires sharing attention, but this sharing of attention is expensive - speed and accuracy are likely to be affected. In addition, there is a limit to the number of objects, locations, or tasks that can be present at the same time. This limited ability affects many everyday tasks; for example, using the car's navigation system while driving generally degrades performance on both tasks (Wickens & Holland, 2000). In addition to sharing attention, we can also shift attention from the current location, facility or task to another. This switch also entails costs, usually on processing speed, since it takes time to unlock and re-launch. Quick switching is usually desirable, for example, when the driver has to shift attention to the vehicle entering the intersection to avoid a collision.

In addition to the need to share attention, the dynamic and highly complex visual characteristics of certain game genres require the player to instantly switch attention from one task to another. Games expect the player to face a number of challenges that can quickly follow each other succession. Many situations require an unexpected turn of attention, such as in the case of a sudden attack, when the player's attention on the navigation task has to be paused to deal with an immediate threat. Quick focus away from the current task and quick interaction with the new task are often difficult for novice players. After a certain amount of practice with video games requiring split attention or task switching, the player's ability to share and switch attention is usually improved, and this improved ability can be carried over to support other neon tasks in the real world.

III. CONCLUSIONS

Playing video games can change the brain, perhaps more often than not (Ferguson, 2007). Playing games, in particular create improvements in sensory, perceptive and spatial cognitive functions that are different from the experience gained in the game. The size of the visual field of attention increases (Feng et al., 2007; Green

& Bavelier, 2003, 2006c; Spence et al., 2009) and other functional improvements are observed in the main spatial problems (Green & Bavelier, 2003, 2006c, 2007; Li et al., 2009) and complex spatial problems (Feng et al. 2007), in addition, improvements have been maintained for a long time (Feng et al., 2007; Li et al. In 2009; Spence et al., 2009). These results have profound scientific and educational implications. Studying the effects of playing video games is a new approach to studying long-distance transmission in the learning process and can stimulate the development of new methodologies to study the mechanisms of the brain that are responsible for these effects. Principles based on studying the role of video games in the process of modifying processes in spatial cognition may eventually revolutionize the teaching of spatial skills and concepts to children and even reduce or eliminate gender differences in spatial cognition. Improvements of this kind in basic education will have significant social and economic consequences. At the other end of the educational continuum, new methods of cognitive learning, based on video games for action, can help preserve or even improve spatial cognition as you age. Although the basic science has yet to be done, and although the basic mechanisms of the brain are still only partially understood, the study of the effects of learning computer games desıgnıng is an important and innovative way of exploring learning processes in spatial cognition.

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