information to rectify the initial contour, then the initial contour is embedded into a higher dimensional function, i.e. Level Set function and evolved toward the tongue body. The experiment results demonstrated that the geometric model can find the saltatorial points and correct them, and rectify the contour such that the converged boundary excludes the lower lip well.

In our future work, we will concentrate on separating tongue coating and tongue quality, doing quantitative analysis of the colors and texture of the tongue, the thickness of its coating and the cracks of the tongue. Finally, we will build a physical examination system according to features of the tongue and the relations between the features and the diseases based on TCM principle.

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A PRACTICAL EEG STUDY ON AUTISM USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Autism is characterized as a spectrum of neurodevelopment impairments in communicative, social behavioural, and sensory motor skills. Public concerns about autism have grown in recent years due to the prevalence of its diagnosis in 1 out of 150 young children. Though many researches have been carried out to analyse autistic patients' EEG behaviour, an effective physiological diagnosis for autism does not exist and researchers haven't found a distinguishing pattern to classify autistic and non-autistic subjects. This preliminary study analyses the EEG data to compare patterns of speech and non- speech sound discrimination between 8 non-autistic and 4 autistic teenagers.

An Artificial Neural Networks (ANNs) based classifier has been implemented to determine whether EEG data reflects differences from the two types of responses.

KEY WORDS

Autism, MMN, artificial intelligence, classification, and neural networks

1. Introduction

1.1 Autism

The cause of the social interaction impairments that universally inflict children with autism still continues to elude both scientists and clinicians [1]. Autism falls under the larger category of autism spectrum disorders (ASD) that characterizes a diagnosed individual with a unique range of developmental impairments in communicative, social behavioral, and sensory motor skills [2]. The diagnosis of autistic individuals ranges from lower-functioning infantile autism to a higher-functioning case like Asperger syndrome, depending on the combination and severity of an individual's impairments. Higher-functioning autistic individuals may possess superior language skills and mental capacity, but they often lack the social behavioral skills needed to respond appropriately to verbal and visual cues during social interaction. However, previous studies have shown that autistic children respond more readily to non-speech, musical [3] and non-social sounds [4]. Čeponienė *et al.* [5] has discovered that higher-functioning autistic children discriminate non-speech tonal changes much better than

speech sound changes in st
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stimuli significantly depend
consisted of a speech or no
prompts this present study
discrimination responses
stimuli among autistic and n

The significance of compari
responses among autistic an
the possibility of discoveri
of behavior in both groups
can then provide the basis
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and/or confirm the psychol
children at a younger age.
autism also does not exist,
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mainly on classifying mo
autistic children who can ve
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1.2 Mismatch Negativity (

In order to determine the be
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other hand, Nätäänen [8] has introduced the method of analyzing sound discrimination responses with mismatch negativity (MMN) data from electroencephalogram (EEG) testing that elicits data from subjects in their conscious state. MMN depicts the evoked potentials that are elicited by a subject's involuntary neurological response to discriminating the incidence of deviant sounds that interrupt a repetitive onset of standard sounds stimuli Because eliciting MMN data does not require subjects to pay attention or perform specific tasks, the MMN method allows researchers to effectively obtain data from autistic children who may have short attention spans and difficulty in following directions.

1.3 Responses to Social versus Non-Social Speech Sounds

Although many MMN studies have yielded conclusive results for auditory sound discrimination in autistic children [5, 9, 10, 11], these previous studies have not specifically compared the subjects' responses to both social and non-social speech sound stimuli. Lepistö *et al.* [9] compared the discrimination of speech and non-speech sounds in children with autism using MMN, but it focuses on pitch changes within each type of sound stimuli in order to also analyze for sound encoding and attentiveness. The study concluded that children with and without autism responded similarly to the pitch changes of social speech vowel sounds and their non-speech components, except that children with autism had a shorter MMN latency response to the non-social speech sounds. These results prompt us to determine whether or not removing the pitch changes in the sound stimuli would provide more conclusive analysis about how each subject group discriminates social and non-social speech sounds, since the pitch changes are meant to analyze attentiveness. Ferri *et al.* [10] studied the MMN responses of lower-functioning autistic children with autism, but whether their study's sound stimuli involved social or non-social sounds remain unclear. Kuhl *et al.* [11] compared responses to speech and non-speech sounds in the auditory preference portion of their experiment, but not in the event-related potential test portion that would provide sound discrimination results. Dawson *et al.* [12] have compared responses to social and non-social stimuli among children with and without autism, except that the study involved visual stimuli instead of sound stimuli. Their study concluded that children with autism failed to attend to both types of stimuli to a higher degree than the other groups of children. More importantly, it also found that children with autism failed to attend to social visual stimuli even more prominently than non-social visual stimuli. Instead of using visual stimuli, this present study aims to compare the elicited MMN responses to speech and non-speech sound stimuli in both autistic and non-autistic adolescents using speech and non-speech sounds.

1.4 Neural Networks in Classifying Autism

Once the MMN data is obtained, an artificial neural network (ANN) will be used to develop a classification algorithm that can potentially classify random individuals as either autistic or non-autistic, based on their sound discrimination of social and non-social speech sounds. A few precedent studies have involved using ANNs to either classify or examine the attention deficits of children with autism. Cohen [13] introduced the use of an ANN to classify children with autism and mental retardation. His method involved surveying the caretakers of the children diagnosed with autism and mental retardation in order to collect scaled responses on a set of chosen classification criteria. Subsequent studies involving ANNs to analyze children with autism have involved the use of self-organization maps (SOMs) to classify responses to different stimuli [14, 15]. Although SOMs may be effective in showing the spatial relationships of its data inputs, this method does not provide a means of classification. Thus, this present study aims to apply a similar ANN classification method but focus on evaluating sound discrimination response data obtained directly from autistic and non-autistic subjects. More specifically, the ANN data inputs will involve the use of statistical features that characterize the entire set of EEG data obtained from the experiment.

1.5 Summary

Using a statistical analysis of EEG data that depicts social and non-social speech sound discrimination in autistic and non-autistic children, this study aims to develop an ANN to classify autism in children between the ages of 11-17 years old. This proposed classification system makes a few major assumptions. First, it assumes that distinct sound discrimination response patterns exist between autistic and non-autistic individuals. Secondly, it presumes that a larger population of autistic adolescents will exhibit the same sound discrimination characteristics as the sample of autistic subjects involved in this study, and vice versa for the sample of non-autistic children. Lastly, it asserts that utilizing the entire set of EEG data obtained in response to speech and non-speech stimuli will be as effective as extracting only the relevant MMN amplitude and latency data. In light of these assumptions, the importance of distinguishing such patterns from the sound discrimination data lies in its potential to diagnose autism as early as infancy so that algorithms can be developed to help diagnose autism. Ultimately, this would allow earlier interventions for autistic children in the areas of communicative and social behavioral impairments.

2. Problem Statement

Is it possible to detect autism in children based on auditory ERP tests? To provide an answer, one must first respond to the following questions:

1) Which indicators could distinguish patterns in the

EEG associable with each of the two categories (autistic/non autistic child)?
2) How to deal with large dataset for the analysis?
3) How can the data be compressed without losing valued information?
4) Can an accurate classifier be found to discriminate EEG of autistic from non-autistic behavior?

The EEG data of each subject contains more than 1000 ERP events properly labeled across the file. Six electrodes (C3, C4, Cz, F3, F4, and Fz) are considered for each subject file. The resulting data sets are so large that this can not be directly used without pre-processing. Not every point of the data can be used individually to train a classifier. Thus feature extraction is performed to simplify the set without sacrificing critical information.

After data set reduction, an Artificial Neural Network is designed to generate a classifier based on these statistical features. Testing results are collected and a performance analysis is performed to evaluate the merit of this ANN-based approach.

3. Methods

3.1. Data Collection

3.1.1. Participants

In this study, 12 subjects were considered. These considered 4 Autistic teenagers are from mid-functioning to high-functioning, who were unmedicated, and had no EEG, MRI, or chromosomal abnormalities; and 8 non-autistic teenagers (psychological and experimental) as the control group. All subjects in both groups were mainly English speakers with normal hearing. All the tests were conducted at the Miami Children's Hospital Brain Institute.

3.1.2. Stimuli and Experimental Design

The stimuli used were the vowels "la", and "bla" and their non-speech counterparts. The vocal tract models were extracted of the vowels "la" and "bla" produced by a female speaker. In each stimulus block, the frequent, "standard" stimulus "la" and the infrequent, "deviant" stimuli "bla" were presented in random order. The stimuli were presented stereophonically via loudspeakers. The same procedure is applied with non-speech sound. During the experiment, subjects were instructed to sit still, watch silent cartoons on a laptop monitor to achieve stable vigilance, and pay no attention to the sounds. The duration of the experiment was approximately 1.5 hours with 2 sections: stimulus 1where the speech sound denoted as ST1 and stimulus 2, the non-speech sound, which is denoted as ST2. In all experiments, the stimulus delivery was controlled by the PC-based NeuroStim program from NeuroScan Inc.

3.1.3. EEG-Recording and Averaging

The EEG (amplified by SynAmps, band pass 0.15–50 Hz, sampling rate OF 250 Hz) was recorded using silver/silver–chloride electrodes at F3, C3, (left hemisphere), Fz, Cz, (midline), and F4, C4 (right

hemisphere), according t
and vertical and hori
monitored by recording
electrodes placed below
right eye. During the ex
was attached to the nose.

EEG epochs of 1100 n
stimulus baseline time, w
for each stimulus class. A
points are obtained in ea
exceeding 100 μv in a
omitted from the averagi
recorded for each subject,
accepted for averaging. T
with 1–15 Hz band-pass.
for frequent and rare sti
Difference waves were
responses to the standar
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standard stimuli right afte
when averaging. These
presence of MMN to devi
which were then exported
is how all the six aver
under each stimulus were

3.2. Feature Extraction

Feature extraction was de
reduce the size of the da
each channel (C3, C4, C
compute a grand averag
subject. This way, 2 gra
each subject were obtain
separately. Each one cons

To allow for simplificati
analyzed regardless of
allowed to focus merely
e.g. on the histogram of t

The following paramete
grand averaged wave as
processing was done usin

Notation: n is the data
measurement value of the
at point i. $\bar{x}$ is the sampl

Mean: It is computed as

$$\bar{x}=\frac{1}{n}$$

Peak: It is the highest va

$$x_{max}=\max\{x_i\}$$

Standard Deviation: It is
estimation of the variance

$$\sigma=$$

Skewness: It is a measure

$$s=\sqrt{n}\,\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^3\left[\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2\right]^{-3/2} \qquad (4)$$

Kurtosis: It is a measure of the "peakedness" of a histogram:

$$k=n\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^4\left[\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2\right]^{-2}-3 \qquad (5)$$

Spectrum Power: It is computed as the average square of the Fourier Transform F:

$$SP=\frac{1}{n}\sum_{w=1}^{V}F^2(w) \qquad (6)$$

where $F^2(w)$ is the magnitude of the Fourier spectrum for a specific frequency w.

3.3. Classifier Implementation

3.3.1. Training Set Preparation

After averaging the 6 channel EEG signals of each subject, a mean average file was created, from which the mean, peak, standard deviation, skewness, kurtosis and spectral power values were computed under stimuli ST1 and ST2. Thus, the training set consists of 12 dimensional patterns according to the extracted features as shown on table 1, where each pattern represents a different subject. Target values were set to 1 or -1 so as to represent autistic and non autistic children, respectively.

The features and terms are denoted as follows:

- ST_1: Stimulus 1 which is speech sounds
- ST2: Stimulus 2 which is non-speech sounds
- M_1: Mean under stimulus ST_1
- M_2: Mean under stimulus ST2
- H_1: Peak under stimulus ST_1
- H_2: Peak under stimulus ST2
- STD_1: Standard Deviation under stimulus ST_1
- STD_2: Standard Deviation under stimulus ST2
- S_1: Skewness under stimulus ST_1
- S_2: Skewness under stimulus ST2
- K_1: Kurtosis under stimulus ST_1
- K_2: Kurtosis under stimulus ST2
- P_1: Spectral power under stimulus ST_1
- P_2: Spectral power under stimulus ST2
- Class -1: Negative detection, non-autistic subject
- Class 1: Positive detection, autistic subject

Table 1: Training set showing first 6 features (S: subject number)

S	M_1	M_2	H_1	H_2	STD_1	STD_2
1	0.7256	-0.4260	3.9311	2.9082	1.2394	1.2996
2	1.3570	2.5788	4.3359	9.2187	1.6212	2.0434
3	1.4264	-0.7938	4.0154	7.8260	1.2834	2.6842
4	-0.0462	-0.5617	2.6832	5.0749	1.1223	1.9215
5	0.9874	1.0537	4.3591	4.0654	1.5900	1.3532
6	-1.1937	-0.6688	1.3435	2.9226	0.7457	1.8477
7	-0.0885	0.1133	2.2766	2.6088	1.2235	1.4471
8	2.4744	-1.1419	5.4900	1.7285	1.3332	1.2856
9	0.4429	0.5781	3.1080	9.7086	1.2980	3.1318
10	-0.5753	0.1276	1.4718	1.8587	1.1277	0.8946
11	-0.5458	0.6236	1.3112	5.8564	0.8196	1.5940
12	-1.0555	4.3215	2.4343	14.8550	1.3298	4.3917

Table 2: Training set continued with the last 6 features and target (S: subject number, T: target)

S	S_1	S_2	K_1	K_2	P_1	P_2	T
1	0.13	0.11	2.35	2.93	567.75	514.54	-1
2	-0.30	0.95	2.27	5.30	1231.10	2983.80	-1
3	-0.38	0.47	3.70	4.50	1014.50	2155.20	-1
4	0.17	0.50	2.79	3.75	346.96	1102.40	-1
5	0.08	-0.18	2.62	3.20	964.34	809.97	-1
6	0.64	0.02	4.01	2.07	546.16	1062.30	-1
7	-0.28	0.0	2.14	2.00	413.82	579.40	-1
8	-0.11	-0.20	2.97	2.34	2178.70	814.39	-1
9	0.08	0.71	2.17	5.35	517.45	2789.60	1
10	-0.82	-0.16	3.07	2.16	441.09	224.57	1
11	-0.46	0.85	2.72	3.95	266.95	806.03	1
12	0.71	0.78	3.04	2.75	793.77	10458.00	1

3.3.2. Dataset Partitioning and Training Strategy

Due to the limited numbers of subjects used in this study, special attention had to be given on to how to exploit the data during training and still obtain a classifier able to generalize well. To that end, 50% of the set was reserved for training and the remaining 50% for testing. Training was performed with crossvalidation, e.g., a portion of the 50 % used in training is actually used for training whereas a small portion of this 50 % is at times used to crossvalidate the classifier and to early stop the iterations (see Fig. 1). Crossvalidation is a general strategy used to avoid memorization and increase the generalization ability of the classifiers. The distribution of patterns during training is shown in Table 3.

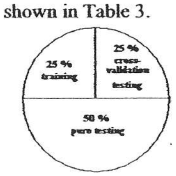

Figure 1: Data partitioning for classifier generation

Table 3: Patterns as distributed during training

Subset	Subjects in the Subset
#1 (25% training)	1 Autistic (Subject 9); 2 Normal (Subject 1,2)
#2 (25% cross testing)	1 Autistic(Subject 10); 2 Normal (Subject 3,4)
#3 (50 % pure testing)	2 Autistic (Subject 11,12); 4 Normal (Subject 5,6,7,8)

3.3.3. Classifier Generation

3.3.3.1. Network Design and Training

A number of paradigms can be used as classifiers for pattern recognition, such as Support Vector Machines, ANN, Fuzzy Logic classifiers, to name a few. For this study, ANNs were chosen due to the applicability of neural studio, a platform that was developed in the CATE center of FIU (Center of Advanced Technology and Education of Florida International University)

Based on the data used, the following ANNs architecture as illustrated in Figure 2 was developed to optimize the classification process.

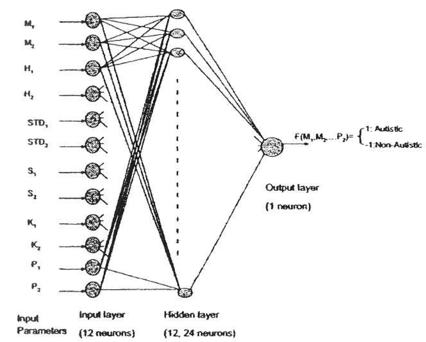

Figure 2: Proposed ANN configuration architecture

This architecture is a feedforward multilayer neural network [16] consisting of an input layer; a hidden layer and an output unit which will provide the classification value (see Figure 3). The parameters in the training tables were used in configuring the ANNs architecture. The proposed configuration 12 -X -1 means the network will have 12 input neurons, a variable number of neurons in the hidden layer, and one output neuron. The amount of hidden units was varied in this study in an effort to find a simple configuration that would minimize the classification errors. Furthermore, input units were assigned zero bias and a linear transfer function was used, whereas hidden units and output unit used a sigmoid transfer function.

The network was trained with the backpropagation algorithm [17].

3.3.3.2. ANN Implementation of NeuralStudio

For implementation, Neural Studio software [18] was used, a computer program developed at the center for advanced technology (CATE) from Florida International University (FIU). NeuralStudio is a powerful and state-of-the art tool for conducting research on ANN's. It offers modules for the analysis of the most popular ANN's as well as assistive tools for database analysis, including a wide range of configurable visual outputs and the ability to stop the calculations for temporal results visualization.

4. Results

The classifier was trained for two different ANN configurations, namely 12-24-1 and 12-12-1. The first configuration was an attempt to follow the rule of thumb that proposes twice as many hidden units as there are input units. Given the relative large number of hidden units (12) another version with fewer units was tried.

Optimum weights are not shown in this paper for space considerations, but they can be easily re-created.

Performance evaluation of the classifier was conducted by a differential investigation based on Receiver Operating Characteristics (ROC) analysis [16].

An ROC analysis is started with a confusion matrix which contains information about actual and predicted classifications done by a classification system. The

following table shows the e
for a two class classifier.

Table 4: Entries

Actual	Positive	
	Negative	

True and false refers to the
respect to the actual state
norm, this case study co
existence of the disease
presence of the disease.

The accuracy (AC) is the
of predictions that were cor
equation:

$AC = \frac{}{TP}$

The classification error is d

$CE = \frac{F}{TP+TI}$

The confusion matrices obt
the 12-24-1 and the
configurations are illust
respectively. For subset con

Table 5: Confusion matrixes obta
1 configuration. Positive and neg
and (-),

Subset		
#1 (training)	Actual	(+ (-
#2 (cross testing)	Actual	(+ (-
#3 (pure testing)	Actual	(+ (-

From the three matrixes
important overall indicator
involved in the study. Thu
91.67 % and the total classi

Table 6: Confusion matrixes obta
1 configuration. Positive and neg
and (-),

Subset		
#1 (training)	Actual	(+ (-
#2 (cross testing)	Actual	(+ (-
#3 (pure testing)	Actual	(+ (-

The overall indicators for
for the total accuracy AC
classification error CE =
performance of the classifi
of hidden units is decrease

5. Discussion and Conclusion

The results of this study indicate distinctive patterns of speech and non-speech sound discrimination among autistic subjects with varying moderate to high-functioning communicative abilities and non-autistic subjects. As it can be seen from the results, using Artificial Neural Network as a method to discriminate autistic subject from non-autistic subject according to their EEG response to speech and Non-speech stimulus is feasible. These results would be statistically meaningful if more subjects were included.

This study is a pilot project trying to find a novel way to classify autism. Given the fact that MMN and P3a are two important features of Autistic ERP, it is expected that their inclusion into future studies would improve the classification accuracy.

The present results show that autistic teenagers do have different EEG response to speech and non-speech sounds from the non-autistic teenagers, not just presented in MMN and P3a, but also through the statistic features used in this ANNs approach.

The results also show that more hidden neurons (24) increase the accuracy, but at the expense of additional processing time for the ANNs to converge.

In these preliminary results, only a small number of subjects were available for this study, the confusion matrixes reveal excellent classification results. The merit of the parameters used (mean, standard deviation ...) would of course be better assessed once more subjects are recruited into this study.

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CAN EEG PROCESSING REVEAL SEIZUR

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ABSTRACT

Epilepsy is characterized by an unexpected and frequent malfunction of the brain. Electrical activity in the brain has been studied for years in an attempt to predict seizures. This paper processes raw intracranial EEG recordings from different subjects in the time prior to seizure.

A set of indicators is extracted from non-overlapping scrolling windows of 1 sec duration. The objective was to identify patterns that reveal that a seizure is developing before it occurs.

While the exhaustive analysis did not detect patterns appropriate to predict a seizure, some indicators were observed to behave in time more similar independent of the subject. Similar time evolution was found for the activity and the power of the alpha and delta bands. It is also shown that the behavior of the correlation integral is somehow similar minutes before the seizure.

KEY WORDS

EEG, Epilepsy, Seizure prediction.

1. Introduction

The National Institute of Neurological Disorders and Stroke estimates that more than 2 million people in the United States have experienced an unprovoked seizure or been diagnosed with epilepsy. For about 80 percent of those diagnosed with epilepsy, seizures can be controlled with some medicines.

EEG has been studied for years in an attempt to predict seizures. Anything that disturbs the normal pattern of neuron activity can lead to seizures.

In the area of epilepsy, where the most important goal is to predict seizures, different measures have been used for years, without much success to produce reliable, prospective seizure prediction [1, 2]. This outcome is quite understandable given the challenge imposed by such a critical research endeavor. In the context of this study, many of the methods currently available in the specialized literature have been tested yielding contradictory results. In an effort to compile all methods and conduct a detailed investigation on EEG data towards seizure prediction, this

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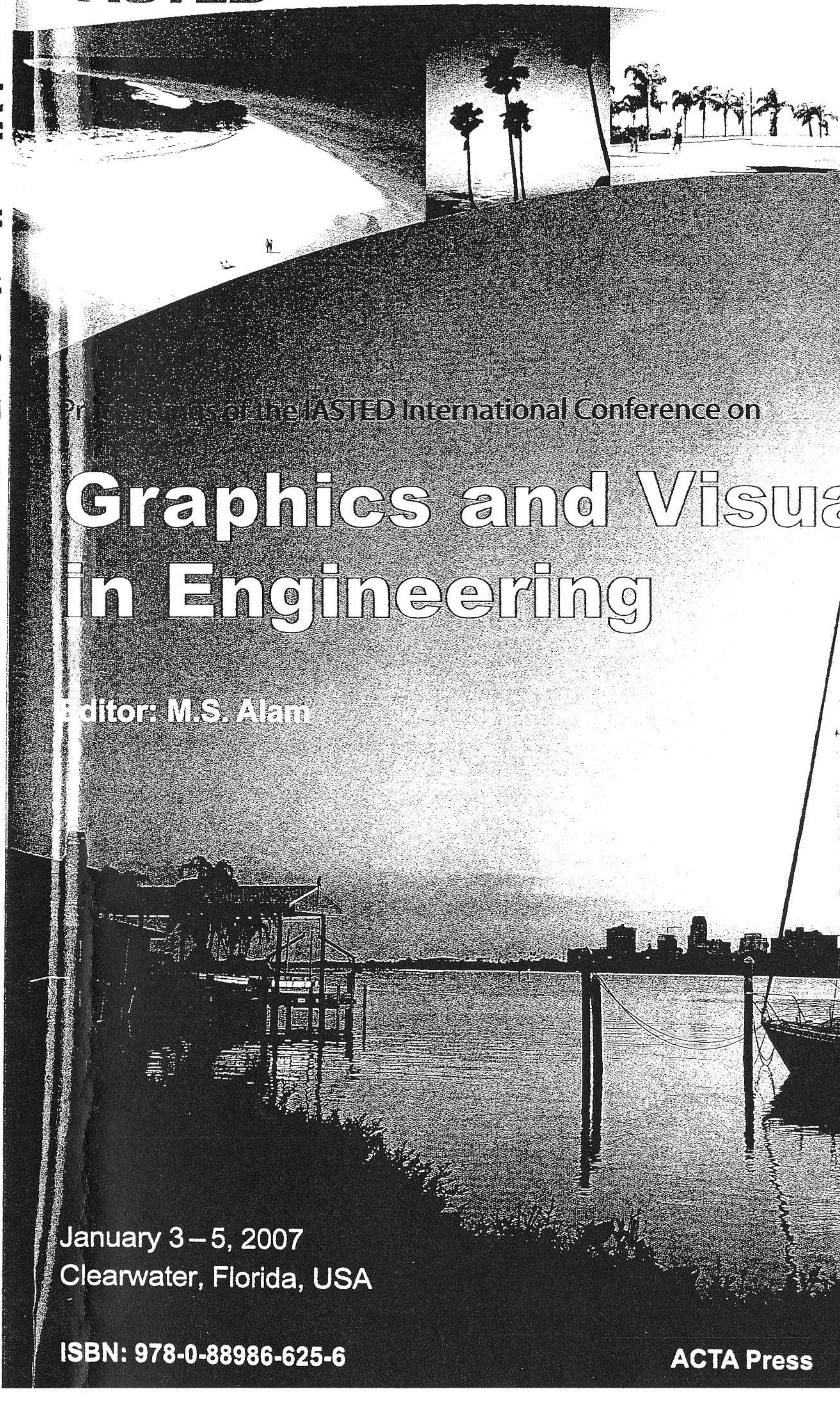

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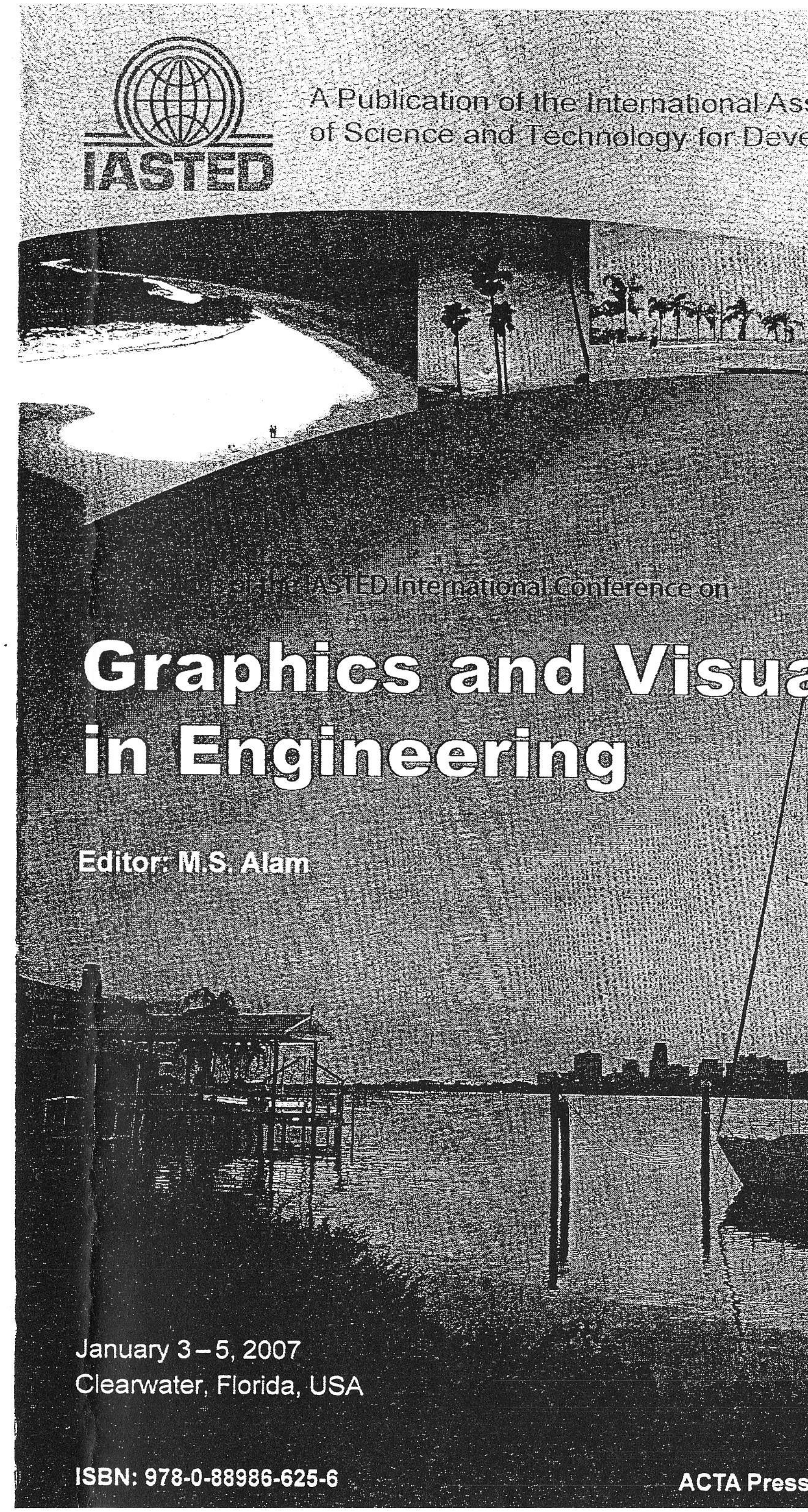

$$\begin{aligned} \mathrm{comm}_{\mathrm{Maxwell}}(n) &= [A, \partial/\partial t\ A] / \sqrt{n} \\ &= 0 / \sqrt{n} \\ &= 0 \end{aligned} \tag{11}$$

We are interested in the limiting case

$$\lim_{n \to \infty} (\mathrm{comm}_{\mathrm{QED}}(n) - \mathrm{comm}_{\mathrm{Maxwell}}(n)) = 0 \tag{12}$$

For a system that has a very large number of photons, the quantum commutator behaves like the classical commutator, demonstrating that the limiting case of QED is Maxwell's equations. In most applications the number of photons actually is quite large and so the system behaves classically. But the quantum nature of the photon is always present, and is even evident in certain macroscopic systems (like the photoelectric effect), where Maxwell's equations cannot begin to explain the phenomenon.

How large is large for the number of photons? In the visible spectrum, red light has a wavelength λ of roughly

$$\lambda \sim 6 \times 10^{-7} \mathrm{m}$$

The energy $\mathcal{E}$ (in joules $\mathcal{J}$) of a single "red" photon is

$$\mathcal{E} = h\frac{c}{\lambda} = 3 \times 10^{-19} \mathcal{J}$$

Using a light source with power of 1 watt (1 $\mathcal{J}$/sec), the number n of photons emitted per second is $1/\mathcal{E}$, or about 3×10^{18}. So even in a dimly lit scene, we expect a conventional (classical) renderer to produce accurate. That comes as no surprise; the point here is that we can quantify why classical illumination is good enough.

In order for the quantum field properties of photons in a rendered scene to make a difference, we must consider a situation where there is only a small number of photons. This can occur if the time interval for the light to be collected must be very small; or the light source is very dim; or the illuminated volume is very large so the photon density is low; or the rendered volume is a very small subset of the total space, containing only a few localized photons; or the wavelength of the light is very short but energetic (which means rendering a scene illuminated by gamma rays).

5. Conclusion

We summarized the essentials of quantum electrodynamics (QED) that are needed to relate it to classical electrodynamics. In brief, the photon states form a Fock space and are represented by linear combinations of kets and are acted on by a quantum field operator *A* defined via the least action together with a commutator relation. When the number of photons is large, the effect of the quantum commutator is negligible, and it asymptotically approaches the classical commutator for the vector potential A. It is in this sense that QED approaches classical electrodynamics as presented in Maxwell's equations.

Acknowledgments

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AUTHOR INDEX
GVE 2007

A

Abu-Raddad, L. *137*
Adjouadi, M. *41, 47, 68*
Alam, M.S. *53*
Austin, J.A. *74*
Ayala, M. *41, 47*

B

Banks, D.C. *137*
Barreto, A. *41, 47, 68*
Bonvallet, B. *113*
Buttarazzi, B. *107*

C

Cabrerizo, M. *47*
Charissis, V. *13*
Chenery, C. *101*
Chiu, C.-C. *25*
Cremer, J. *117*
Crouch, J.R. *74*

D

Delgado, J. *68*
Dinniman, M.S. *74*

E

Eppler, M.J. *83*

F

Fourie, J. *95*

G

Griffin, N. *113*
Guillen, M.R. *68*

H

Hong, S. ....

J

Jang, I. ....
Jeon, Y. ....
Jeong, J. ....

K

Ku, M.-Y. ....
Kummert, A. ....

L

Lahlou, M. ....
Lengler, R. ....
Li, J. ....
Li, L. ....
Li, S. ....
Liang, L.-w. ....
Luo, Y.-C. ....

M

Manseur, R. ....
Maskey, M. ....
Meyer, J. ....

N

Naef, M. ....
Newman, T.S. ....
Nguyen, H.T. ....

O

Ohya, J. ....

P

Patera, M. *13*

R

Rishe, N. *41, 47, 68*

S

Sang, J. *53*
Schauland, S. *19*
Shen, Y. *74*

T

Teng, N. *41*
Tito, M.T. *47*

U

Urraci, G. *107*

V

van Zijl, L. *95*
Vrajitoru, D. *89*

W

Wang, L. *41*
Wang, Z. *117*
Watanabe, T. *7*
Won, Y. *131*
Wu, B.-F. *25*

X

Xiao, D. *58*
Xie, Y. *31*
Xu, J. *37*

Y

Yang, D. *37*
Yaylali, I. *47*
You, X. *41*

Z

Zhou, C. *37*
Zhu, X. *53*
Zou, F. *37*