

Diagnosis of OCD Patients Using Drawing Features of Bender Gestalt Shapes

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ABSTRACT

Background: Since psychological tests such as questionnaire or drawing tests are almost qualitative, their results carry a degree of uncertainty and sometimes subjectivity. The deficiency of all drawing tests is that the assessment is carried out after drawing the objects and lots of information such as pen angle, speed, curvature and pressure are missed through the test. In other words, the psychologists cannot assess their patients while running the tests. One of the famous drawing tests to measure the degree of Obsession Compulsion Disorder (OCD) is the Bender Gestalt, though its reliability is not promising.

Objective: The main objective of this study is to make the Bender Gestalt test quantitative; therefore, an optical pen along with a digital tablet is utilized to preserve the key drawing features of OCD patients during the test.

Materials and Methods: Among a large population of patients who referred to a special clinic of OCD, 50 under therapy subjects voluntarily took part in this study. In contrast, 50 subjects with no sign of OCD performed the test as a control group. This test contains 9 shapes and the participants were not constraint to draw the shapes in a certain interval of time; consequently, to classify the stream of feature vectors (samples through drawing) Hidden Markov Model (HMM) is employed and its flexibility increased by incorporating the fuzzy technique into its learning scheme.

Results: Applying fuzzy HMM classifier to the data stream of subjects could classify two groups up to 95.2% accuracy, whereas the results by applying the standard HMM resulted in 94.5%. In addition, multi-layer perceptron (MLP), as a strong static classifier, is applied to the features and resulted in 86.6% accuracy.

Conclusion: Applying the pair of T-test to the results implies a significant supremacy of the fuzzy HMM to the standard HMM and MLP classifiers.

Keywords

Bender Gestalt, Optical Pen, Fuzzy HMM, OCD, Psychology

Introduction

Psychologists utilize some gold standard tests in the form of questionnaires or shape/object drawings to qualitatively measure disorders of their patients. Questionnaire-based tests are more accurate than drawing ones due to having several dichotomies expressed in some levels (e.g. from very low to very high) and finally a total score is calculated as the degree of that disorder or psychological disease [30]. On the other hand, some of the psychological tests are taken by drawing some shapes/objects or even drawing his/her family members. Although drawing-based tests provide a better way of interaction with the patients to reflect his/her emotion, stress or anxiety, the scoring value

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of these tests cannot be determined as easy as that of questionnaires. Moreover, the key data such as speed, pressure, curvature, pen angle with different directions that reflect the spirits of the patients in terms of stress, anxiety, fear, happiness and anger are lost after drawing each shape; consequently, the evaluation is done just based on the visual inspection and the resulted score carries a high degree of uncertainty.

Some of these test include Yell-Brown, Bender Gestalt, Rorschach [1-2], Koppitz's Human Figure Drawing (HFD) criteria, in which the drawn shapes by the patients need to be investigated by a psychologist; however, different psychologists may give different scores to an executed test that lead to involve a degree of subjectivity. Among the mentioned tests, Bender Gestalt has a good potential for measuring the Obsession Compulsion Disorder (OCD) degree. This test contains 9 different shapes in which each query should draw them. Therefore it would take some minutes for OCD patients to draw.

Based on the statistics, Bender Gestalt results could correctly estimate the degree of OCD up to 80%. This result demonstrates a high degree of uncertainty involving in the diagnosis of the accurate level of this disorder. This insufficient quality rises from the lack of information missed through the test such as time, the amount of pressure that the patient applies to draw each part of the shapes, the angle of pen with the perpendicular vector to the page, the amount of curvature, the angle of pen with the X-axis, etc. It should be noted that in order to use all information for the diagnosis, some attempts have been made to utilize these missing features by employing an optical pen equipped with several sensors measuring and recording quantitative features while a subject writes or draws a shape.

The main application of this approach which has been commercial, is signature and handwriting verification by moving an optical pen by the subject on a digital tablet. There are

some international banks asking their customers to sign the bills by the optical pen [9]. In addition, there are some websites that you can purchase the stuff online, but to increase the security in this financial transaction, when you want to enter your bank account to the website, there is an obligatory option that you should sign by optical pen on the tablet at your home/office to verify your identity [26-28]. Handwriting recognition [3,5] is another application that can verify the identity of the person who writes a text. The base of these applications lie in the fact that it is possible that someone imitates another ones' signature or handwriting but during the drawing or writing, he cannot copy that exact pressure and pen angles that the original one does. Unlike the simplicity of use of this tool, its results appear very secure and efficient in real applications [9].

Regarding the dynamic nature of such input sequences, it is obvious that dynamic models are the best alternatives to handle the time warping through the sequence. There are some classifiers such as Multi-Layer Perceptron (MLP)/Radial Basis Function (RBF) neural networks [12,20], Support Vector Machine (SVM) [17,29] and Fuzzy Rule Based Classifiers (FRBC) [15,21] which have unique positive properties such as general/local approximation and flexibility, minimizing the expected risks and interpretability along with good handling of uncertainty, respectively.

Although these classifiers act successfully in real applications, none of them is naturally constructed for a stream data with statistic changes through time. These classifiers are designed for static applications in which time does not affect the distribution of features. For those applications in which their input data distribution varies with time, state-based decision makers such as Markov chain, Hidden Markov Model (HMM) and Bayesian network are used. Although the incremental version of static classifiers such as Incremental SVM [17,29], Time Delay Neural Network (TDNN) [13-14] are developed, they are very time

consuming and complex in implementation; therefore, dynamic based classifiers act better in practice.

To the best of authors' knowledge, there is no similar attempt to make psychological tests quantitative and this is the first study which investigates the usability of optical pen to increase the performance of these tests. Since OCD has a high prevalence among people, Bender Gestalt test is chosen to be enhanced by adding the drawing features that are all missed through a classic execution of the test. Regarding novelty of this approach, no database is found on the internet; consequently, a standard database is collected through this research. This dataset contains features of 50 control subjects and 50 OCD patients who draw all of the Bender Gestalt shapes.

HMM is still a state-of-the-art classifier in signature verification, speech processing and handwriting recognition; therefore, it can be a good candidate for our application. Despite all positive properties of semi-continuous HMM, its learning criterion (expectation maximization) is a bit solid and a fuzzy approach is employed to increase the flexibility of the learning process [3]. Afterwards, the achieved results by fuzzy HMM decision maker is compared to that of the achieved by HMM and neural network in order to show the effectiveness of the proposed approach. The rest of this paper is organized as follows: Section 2 describes the collected dataset, Section 3 introduces the implemented methods on this paper, Section 4 expresses the evaluation methods and the criteria that the performance of the implemented methods is assessed based on. Section 5 demonstrates the achieved results and discusses the advantages of each method along with their shortcomings. Finally, the paper is concluded in Section 6.

Bender Gestalt Test and Data Acquisition

Obsession Compulsive Disorder is one of the well-known disorders that many people

are suffering from it. The percentage of people in different societies who have OCD is fairly equal and high as well. There are some psychological tests such as Yale Brown test [24, 25] to measure OCD degree in which the Bender Gestalt is more accurate and unlike its time-consuming process, psychologists almost rely on it. The Bender Gestalt test firstly is used as a tool for screening the probability of any insane brainwork. Nevertheless, measuring and judging this test is postponed to the time when a subject draws all 9 shapes and during the drawing, no one measures anything. In other words, psychologists finally compare the original patterns to the drawn ones and this type of judging would miss lots of information such as the amount of pressure that each subject applies to the paper when he is drawing the shapes. Figure 1 shows the specific shapes that Bender and Gestalt designed them to measure the degree of OCD.

To assess the patient not only when he draws all of the shapes but also he takes the test, an optical pen & digital tablet Wacom (STU 520A) are bought which is shown in Figure 2 along with the licensed software Pen Analyst that can measure the following parameters through the drawing process: the angle between the pen and the vector perpendicular to the tablet, angle of the projected shadow of pen of the tablet with the x-axis, time of drawing, pressure at each point of drawing and coordination location of pen at each time on the tablet.

Every day, a lot of OCD patients refer to special clinic for OCD patients in Isfahan. Among patients, just 50 of them agreed to participate in this study. The patients had different degrees of OCD from mild to severe. The patients were asked to draw each of the 9 shapes accurately on the optical tablet. To make the population balance, 50 normal subjects voluntarily participated and drew Bender Gestalt shapes on the digital tablet. The examinees were in different ages (20-60 years old) and genders (60% men and 40% women) with different social and ed-

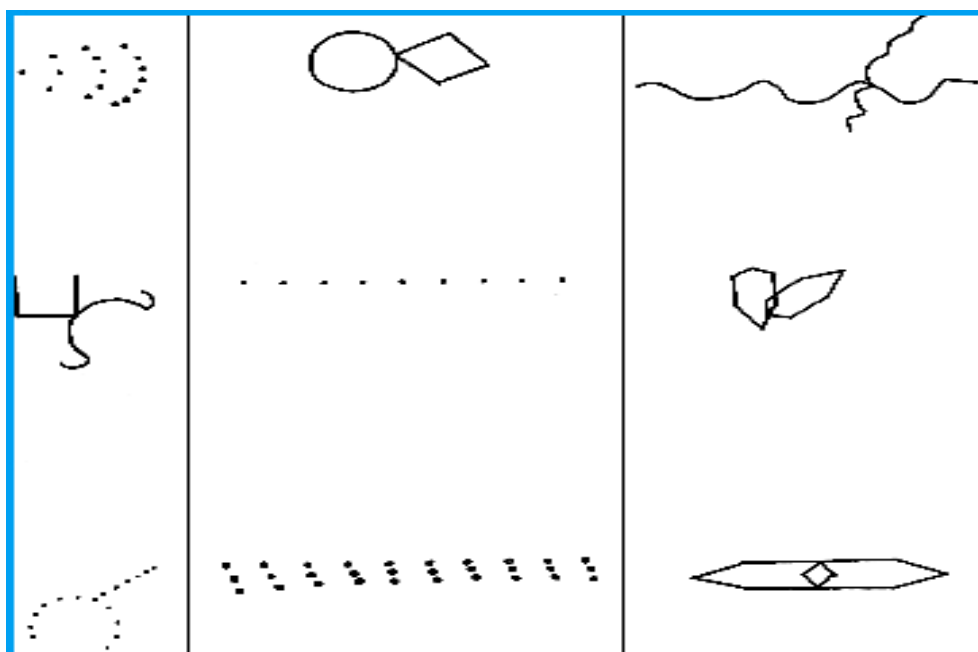


Figure 1: Bender-Gestalt shapes



Figure 2: Optical pen and the digital tablet used in this study (STU 520A)

educational levels (from high school diploma to doctoral degree). When the participants drew the shapes (Figure 1) by the optical pen on the digital tablet, STU 520A took their following five features simultaneously: pressure, time, angles with the perpendicular and horizontal axes and velocity.

After recording all of queries data, the Pen Analyst software converts the raw format of STU 520A apparatus into some scalar matrices where the rows are the drawn features sampled from the continuous painting by 100Hz sam-

pling rate. This sampling frequency is enough for soft margin shapes like the Bender Gestalt ones. The A/D of this apparatus contains 9 bits that is fairly acceptable to store the digitized features in the memory. For instance, STU 520A is able to classify 512 different levels of pressure, velocity and the angles. In other words, each subject produces 9 scalar matrices (each matrix for a shape) and the number of rows is the mentioned five features and the number of column depends on the time that each subject draws a shape. The spatial resolution of the digital tablet is 800×480.

Material and Methods

In this part, the implemented methods which have been executed on the collected dataset are briefly explained. Here, three classifiers were implemented including Hidden Markov Model (HMM), Multi-Layer Perceptron (MLP) and fuzzy HMM. What follows is a brief explanation of the mentioned methods.

Hidden Markov Model (HMM)

HMM is an extended version of Markov chain problem [18] in which the sequence of

the states is hidden. Prior to revealing the sequence state by Viterbi algorithm [16], first, the HMM parameter should be learned via Baum-Welch algorithm [11] which is a learning algorithm for estimating the state parameters of HMM. Therefore, to find the probability of an observation sequence given an HMM model, first the Baum-Welch learning scheme should be applied, then, the suboptimal Viterbi algorithm should be executed to find the suitable state sequence. Finally, the probability of the observation sequence is determined via a simple Markov chain (order 1). The topology of a schematic HMM with 3 states (shown in Figure 3), each state contains 3 five-dimensional Gaussian functions as shown below:

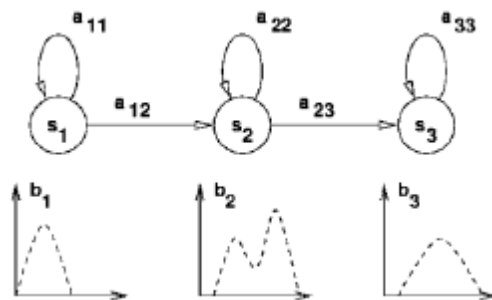


Figure 3: Schematic diagram of an HMM with 3 states

HMMs are almost left to write and just 1 transition is possible for each input observation. To train the topology parameters of a basic HMM, Baum-Welch proposed the three following formulas that recursively iterated to meet the termination criterion which is the expectation maximization. The learning procedure is terminated whenever the probability of the observation sequence giving the new parameters does not exceed that of the previous

epoch. The Baum-Welch formulas are brought as follows:

$$\Pi_i = \text{Expected frequency (Number of times) in state } S_i \text{ (at time = 1)} = \gamma 1(i) \quad (1)$$

$$a_{ij} = (\text{Expected number of transitions from state } S_i \text{ to state } S_j) / (\text{Expected number of transitions from state } S_i) \quad (2)$$

$$b_j(k) = (\text{Expected number of times in state } S_j \text{ and observing } V_k) / (\text{Expected number of times in } S_j) \quad (3)$$

The HMM parameters include $(a_{ij}, b_j(k), \pi_i)$, where a_{ij} is the transition matrix between the states of i and j , $b_j(k)$ is the probability of k^{th} observation at the j^{th} state, and π_i is the initial probability at the i^{th} state. After executing the Baum-Welch algorithm, the Viterbi algorithm is run in order to find the suboptimal sequence of the states. Viterbi optimization is briefly described as follows:

$$\delta_t(i) = \text{Max}_{q_1 q_2 \dots q_t} P(q_1 q_2 \dots q_t, q_t = S_i, O_1 O_2 \dots O_t | \lambda) \quad (4)$$

$$\delta_{t+1}(i) = \text{Max}_i P(\delta_t(i) a_{ij}) b_j(O_{t+1}) \quad (5)$$

$$\psi_{t+1}(i) = \text{argmax}_{i=1, \dots, N} P(\delta_t(i) a_{ij}) \quad (6)$$

where $\delta_t(i)$ is the cumulative forward probability from the first observation till the time t at the i^{th} state. Therefore, at each time t the proper state is determined when both Eqs. (4) and (5) are maximized. In other words, the selected state not only should consider the former states at the time t but also should consider one state further (O_{t+1}) by maximizing the $\delta_{t+1}(i)$. Finally, after finding the proper state sequence, the probability of the input observations given the trained unrevealed (estimated

$$P(O | \lambda) = \sum_{q_1 q_2 \dots q_{t-1} q_t} \pi_{q_1} b_{q_1}(O_{q_1}) a_{q_1 q_2} b_{q_2}(O_{q_2}) a_{q_2 q_3} \dots a_{q_{t-1} q_t} b_{q_t}(O_{q_t}) \quad (7)$$

the state sequence) model is determined by:

where the conditional probability of the observation sequence given the revealed HMM states is calculated based on the multiplication of initial state probability to the probability of being in that state (b_{q_1}) and then multiply to the transition probability from the state#1 to the state#2 ($a_{q_1q_2}$) and this process continues till the transition probability of the last observation vector multiplies to the probability of being the most right state (the model is left to right).

Fuzzy HMM

In order to solve the uncertainty of HMM, a fuzzy HMM algorithm [11] is implemented. Since each state of HMM is expressed in weighted summation of multivariable Gaussian functions, it does not make sense to replace the mixture of Gaussian within each state by some membership functions. Among the states that we are able to incorporate the property, optimization part is the target of this study. In other words, Expectation maximization is used as the termination criterion in which $P(O/\lambda^{new}) > P(O/\lambda^{old})$, where $\lambda = (a_{ij}, b_j, \text{ and } \pi)$ the HMM parameters.

To handle more uncertainty, the learning constraint should be a bit relaxed by incorporating fuzzy smoothness into EM constraint. The fuzzy EM is called FEM and is employed in this study [11]. The description of FEM is explained as follows:

Assuming the joint probability of $P(S/O, \lambda)$ represents the belongingness degree of the observation O to the hidden state of S and denotes it by the following membership function:

$$\{U = [u_s(o) | s \in S] \text{ subject to } \sum_s u_s(o) = 1, 0 < u_s(o) \leq 1 \quad (8)$$

In order to maximize the likelihood function of $L(O, \lambda) = \text{Log}P(O, \lambda)$, the observation vectors $O = [O_1, O_2, \dots, O_T]$ where T is the number of observation vectors, the auxiliary function

$Q_F(U, \lambda)$ is defined as follows where the parameter set of λ is optimized according to this criterion.

$$Q_F(U, \lambda) = \sum_s u_s^F(O) \log P(O, S | \lambda) \quad (9)$$

Where F is a constant ($F > 1$) and this value can regularize the amount of fuzziness. The main objective of FEM is to maximize the $Q_F(U, \lambda)$ on the values of U and λ and finally estimating the pair of (U, λ) such that the following inequality is satisfied:

$$Q_F(\bar{U}, \bar{\lambda}) \geq Q_F(U, \lambda) \quad (10)$$

Multi-Layer Perceptron (MLP) Neural Network

Neural networks are employed in many applications such as classification, prediction and optimization depends on their topology, learning scheme and objective function. Among different topologies, Multi-Layer Perceptron (MLP) is chosen here to be implemented as a strong and flexible classifier [19]. One hidden layer is considered for the employed MLP in order to be capable of handling the high complexity captured through the features stream, to avoid over-fitting and to increase the generalization. Since lots of feature vectors are elicited in this study, cross validation method is utilized to determine the suitable number of hidden neurons. The Tangent-Sigmoid function is selected for the hidden neurons and the pure linear function is selected for the final decision maker neuron. Conjugate gradient descent is selected as the learning scheme due to its learning ability [22].

Evaluation Methods and Criteria

Although lots of participants participated in this study, to remove any correlation between the test and the training sets, to evaluate the trained models by the unseen data, at each fold, all of the elicited feature vectors of one subject should be selected as the test set and the remaining elicited vectors of other partici-

pants are selected as the training set to increase the domain learning of the employed models. It should be noted that 18 separate HMM and FHMM along with 9 MLP models should be trained for the Bender Gestalt shapes. For each of 9 shapes, we need two HMM and two FHMM because one model should be trained for subjects with OCD and one model for normal ones; since we have 9 shapes, 18 HMM and 18 FHMM models should be trained. In contrast, MLP is naturally a multiclass classifier and for each of the Bender Gestalt patterns just one MLP is needed to be trained to classify normal and OCD participants. Incidentally, leave-one (subject)-out (LOO) cross validation method is executed 9 times, each LOO for one of the shapes. As far as 100 participants were taken part in this study, each LOO needs 100 test and train execution. The most important difference between classic Bender Gestalt test and the proposed quantitative version of Bender Gestalt is that the evaluation criterion of the two tests is totally different. In the classic white paper drawing test, psychologists compare the original and the drawn shapes and based on their visual correlation, they make a decision whether the participant is OCD or not. In contrast in this study, no visual correlation is considered as the criterion whereas the correlation of the features of the drawn shapes determines the features of each participant as comparable to the features of normal or OCD groups. This feature correlation measuring is done using the implemented classifiers and this decision should be made for all 9 shapes.

Results and Discussion

In this part, HMM, fuzzy HMM (FHMM) and neural network are trained by the drawn features containing velocity, pressure, time, angle on pen with perpendicular vector to the digital tablet and angle of the project shadow of pen on the digital tablet with the horizontal (x -axis). As we mentioned before, LOO cross validation method is used for evaluating the results and this procedure is performed separately for each of the 9 Bender Gestalt patterns.

Table 1 demonstrates LOO results achieved by HMM and FHMM for each of the 9 patterns,

Table 1: Comparison Results Between HMM and FHMM on the Bender Gestalt Shapes

| Shape No. | HMM Accuracy (in %) | FHMM Accuracy (in %) |
|-----------|---------------------|----------------------|
| Shape # 1 | 95 | 97 |
| Shape # 2 | 92 | 95 |
| Shape # 3 | 93 | 94 |
| Shape # 4 | 91 | 92 |
| Shape # 5 | 93 | 96 |
| Shape # 6 | 90 | 92 |
| Shape # 7 | 88 | 91 |
| Shape # 8 | 87 | 90 |
| Shape # 9 | 85 | 88 |

separately.

As we see in Table 1, the results of FHMM significantly outperformed that of HMM for all of the shapes. The second important point is that as the patients get more tired, their accuracy and patience decreased, that is why as we go down from the top of the table down, the accuracy both for HMM and FHMM decreases. This is not related to the simplicity or hardness of the Bender Gestalt pattern; it just shows the patients wanted to get rid of this time-consuming experiment by the optical pen on the digital tablet. Nevertheless, if we take an average for all 9 shapes, HMM and FHMM results exceed 90% accuracy in average that is better than the statistical results announced by Yale Brown test.

The Bender Gestalt result is reliable just for 80% of the referred subjects. The achieved results imply the effectiveness of quantitative observation of subjects during the test rather than visual comparison of the drawn shape with its original one qualitatively after the test.

As we mentioned in Section 3.3, a two-layer feed forward (MLP) neural network with conjugate gradient decent learning is selected and

its number of hidden neurons at each layer is selected through LOO process. The number of neurons for different shapes was not equal; in other words, depending on the shape complexity, the number of neurons changed. To implement MLP, NPR tool [23] is selected and executed in MATLAB. Applying the drawn features of Bender Gestalt patterns to the trained MLP resulted in a high accuracy for all shapes as shown in Table 2.

Table 2: Results of Applying the Quantitative Drawn Features of the Bender Gestalt Shapes to the MLP Classifier

| Shape No. | Accuracy (in %) |
|-----------|-----------------|
| Shape # 1 | 87 |
| Shape # 2 | 91 |
| Shape # 3 | 90 |
| Shape # 4 | 88 |
| Shape # 5 | 82 |
| Shape # 6 | 87 |
| Shape # 7 | 89 |
| Shape # 8 | 86 |
| Shape # 9 | 80 |

Mean Feature Results

As a simple but efficient trick to both reduce the dimensionality and increase the classification accuracy, features of the elicited drawn features are averaged in each column. Consequently, after this simple feature extraction technique, the feature matrix is converted to a long one dimensional feature vector. As we mentioned, for each shape, two HMMs and two FHMMs were trained for healthy and OCD subjects. The results of LOO cross validation by the averaged features are presented in Table 3.

As we can see in Table 3, FHMM again outperformed the results of HMM for 8 shapes. This supremacy reveals the power of FHMM to handle the uncertainty of HMM. Vividly, the only shape that HMM defeats the FHMM is Shape#8, this is due to the higher com-

Table 3: Comparison Results Between HMM and FHMM on the Bender Gestalt Shapes

| Shape No. | FHMM Accuracy (in %) | HMM Accuracy (in %) |
|-----------|----------------------|---------------------|
| Shape # 1 | 97.9 | 96.1 |
| Shape # 2 | 97.6 | 96.7 |
| Shape # 3 | 97.2 | 95.8 |
| Shape # 4 | 97.9 | 96.5 |
| Shape # 5 | 94.2 | 93.4 |
| Shape # 6 | 96.3 | 95.2 |
| Shape # 7 | 91.2 | 94 |
| Shape # 8 | 91.1 | 92.1 |
| Shape # 9 | 93.3 | 90.9 |

plexity of this shape against others. As we observed, the subjects through drawing the shapes, shape#8 was harder to draw for all participants. Among five features, the time of drawing for this shape was meaningfully higher than the time needed for other shapes. Consequently, this feature affects other ones when an average is taken leading to the reduction of uncertainty; therefore, the standard HMM could outperform FHMM.

Reason of Decreasing Trend of the Results

As we mentioned in the data acquisition part, the queries whether healthy or patient are asked to draw the shapes number one to nine successively. The order of the shapes was all the same for the patients. We observe that the patients and even some healthy subjects were nagging about the time they were allocated to draw the shapes. They all started carefully to draw the shape#1 but after drawing each shape they got tired and impatient and drew the last shapes much faster than the primary ones with less accuracy. That is why, a decreasing trend can be observed in the results from shape number one to nine. Moreover, the results of each shape are taken after drawing that shape but with the features sampled during the painting.

Conclusion and Future Work

In this research, the main objective was to make a qualitative psychological test into a quantitative form by using an optical pen and digital tablet. Here, the apparatus STU520A is prepared and 100 subjects, half of them were healthy and the other half had OCD, took part and their drawing features were recorded during painting the Bender-Gestalt shapes. HMM, fuzzy HMM and MLP classifiers were utilized to assess how the features of subject within each group is similar and how far is the distance of the elicited drawn features of two the groups. The best results produced by FHMM that led to 95.2% while the reliability of the classic Bender Gestalt test is 80%. This supremacy reveals tracing of the drawn features as more important than visual inspection to reveal how the drawn shapes and the original ones are similar.

As for future work, we suggest using dynamic Bayesian network to handle the dynamic drawn features for this and other painting psychological tests. Moreover, incorporating rough set operands along with the fuzzy ones can enhance the flexibility of the combinational classifiers to overcome the uncertainty drawback.

Conflict of Interest

None

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