BFI-Based Speaker Personality Perception Using Acoustic-Prosodic Features

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***Abstract*— This paper presents an approach to automatic prediction of the traits the listeners attribute to a speaker they never heard before. In previous research, the Big Five Inventory (BFI), one of the most widely used questionnaires, is adopted for personality assessment. Based on the BFI, in this study, an artificial neural network (ANN) is adopted to project the input speech segment to the BFI space based on acoustic-prosodic features. Personality trait is then predicted by estimating the BFI scores obtained from the ANN. For performance evaluation, the BFI with two versions (one is a complete questionnaire and the other is a simplified version) were adopted. The experiments were performed over a corpus of 535 speech samples assessed in terms of personality traits by experienced subjects. The results show that the proposed method for predicting the trait is efficient and effective and the prediction accuracy rate can achieve 70%.**

I. Introduction

Research in social cognition has shown that spontaneous and unconscious processes influence our behavior to a large extent, especially when it comes to social interactions with unknown persons [1]. Human presumes personality from the first perception of others in only few seconds, but leads our behavior and attitudes towards that person significantly. In this study, we focused on one aspect of the phenomenon above, the spontaneous, unaware and immediate attribution of personality traits to unknown speakers.

Since the hypothesis of *"speech as a personality trait"* was proposed for the first time in [2], numerous studies have investigated the effect of vocal behavior on personality perception, especially when it comes to acoustics and prosody. According to the human sciences, nonverbal vocal behavior influences personality perception significantly [3].

Recently, many research efforts in speech/multimedia processing, natural language processing and affective computing have focused on emotion recognition and personality traits prediction in order to promote the interaction between machine and human being [4-11]. Conventional personality prediction is termed as Automatic Personality Recognition (APR), which is expected to predict the real personality of an individual. Unlike APR, Automatic Personality Perception (APP) is to predict the personality of a given person as perceived by observers [12]. APP problem is important due to the interactions with unknown individuals are frequent in our daily life. Actually, our behavior is not driven by the real personality of people, but by the traits we perceived and attribute to them spontaneously.

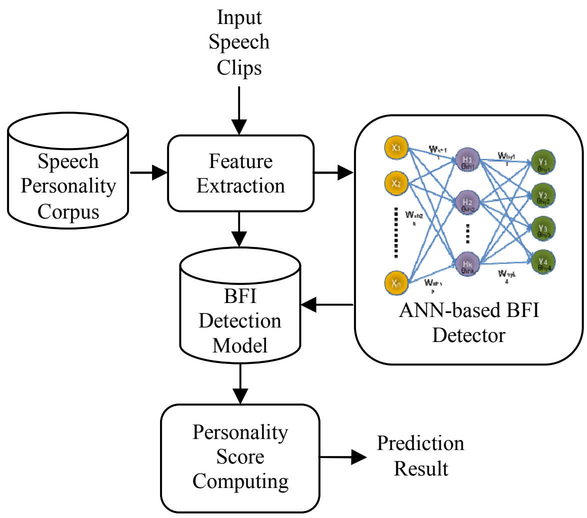

Fig. 1 System Diagram for Prediction of the Personality Perception

This paper proposes an approach to constructing an APP system based on acoustic-prosodic features (e.g., zero-crossing rate, energy, pitch, Harmonics-to-Noise Ratio, Mel-frequency cepstral coefficients, etc.) which are likely to influence personality perception. In psychology, personality assessment is performed using the Big Five Inventory (BFI), a self-report inventory designed to measure the Big Five dimensions [13]. It is quite brief for a multidimensional personality inventory (44 items total), and consists of short phrases with relatively accessible vocabulary. The BFI we adopted in this paper has two versions, one includes 44 items, and the other includes 10 items which is a simplified version. In APP, BFI is used to assess the personality of a given person as perceived by observers, not the real personality of an individual.

The system diagram of the proposed method is shown in Fig. 1. An artificial neural network (ANN) is employed to

TABLE I
THE BIG FIVE INVENTORY QUESTIONNAIRE WITH 44 ITEMS
(AS PROPOSED IN [13])

1.	_____	Is talkative	23.	_____	Tends to be lazy
2.	_____	Tends to find fault with others	24.	_____	Is emotionally stable, not easily upset
3.	_____	Does a thorough job	25.	_____	Is inventive
4.	_____	Is depressed, blue	26.	_____	Has an assertive personality
5.	_____	Is original, comes up with new ideas	27.	_____	Can be cold and aloof
6.	_____	Is reserved	28.	_____	Perseveres until the task is finished
7.	_____	Is helpful and unselfish with others	29.	_____	Can be moody
8.	_____	Can be somewhat careless	30.	_____	Values artistic, aesthetic experiences
9.	_____	Is relaxed, handles stress well.	31.	_____	Is sometimes shy, inhibited
10.	_____	Is curious about many different things	32.	_____	Is considerate and kind to almost everyone
11.	_____	Is full of energy	33.	_____	Does things efficiently
12.	_____	Starts quarrels with others	34.	_____	Remains calm in tense situations
13.	_____	Is a reliable worker	35.	_____	Prefers work that is routine
14.	_____	Can be tense	36.	_____	Is outgoing, sociable
15.	_____	Is ingenious, a deep thinker	37.	_____	Is sometimes rude to others
16.	_____	Generates a lot of enthusiasm	38.	_____	Makes plans and follows through with them
17.	_____	Has a forgiving nature	39.	_____	Gets nervous easily
18.	_____	Tends to be disorganized	40.	_____	Likes to reflect, play with ideas
19.	_____	Worries a lot	41.	_____	Has few artistic interests
20.	_____	Has an active imagination	42.	_____	Likes to cooperate with others
21.	_____	Tends to be quiet	43.	_____	Is easily distracted
22.	_____	Is generally trusting	44.	_____	Is sophisticated in art, music, or literature

model the relationships between acoustic-prosodic features and BFI items, and then the personality of the input speech from an unknown speaker is predicted by computing the scores from the BFI which is obtained from the ANN. Instead of predicting the personality from the speech signal directly, this study estimates the BFI scores for the input speech signal first and then compute the final score for personality perception.

To the best of our knowledge, this study is the first approach to predicting the personality by detecting BFI scores of the input speech from a speaker. Traditionally, personality assessment is completed by manually filling the BFI questionnaire. Automatically predicting the personality perception from speech signal of an unknown speaker is desirable to achieve a comparable result as the assessment based on BFI questionnaire.

Our study shows that the personality trait attribution assessed by human judges can be automatically classified using an ANN-based detector from the vocal cues of speech signal. The experimental results of this work, performed over the corpus of speakers assessed in terms of perceived personality traits, show that it is possible to predict the personality perception by detecting BFI scores with 70%~80% accuracy.

The rest of this paper is organized as follows: Section II introduces personality and its assessment, Section III describes the approach proposed in this study, Section IV provides experimental results and discussion, and Section V gives some conclusions.

II. PERSONALITY AND ITS ASSESSMENT

Personality is the latent construct accounting for *“individuals’ characteristic patterns of thought, emotion, and behavior together with the psychological mechanisms – hidden or not – behind those patterns”* [14]. At present, the Big Five (BF) personality model is the most commonly used and accepted personality model [15]. For this reason, personality assessment used in this study is based on the Big Five Inventory (BFI) [13], a questionnaire intending to score each dimensions in the Big Five Model.

A. The Big Five

The Big Five Personality Model proposes a personality representation based on five traits that have been proved to interpret most of the individual difference. Some research reveals that BF have been identified by employing factor analysis to the large number of words describing personality in daily language [16]. In spite of the variety of terms at character, personality description tend to group into five major clusters corresponding to the BF:

- Extraversion: Active, Assertive, Energetic, Outgoing, Talkative.
- Agreeableness: Appreciative, Forgiving, Kind, Generous, Sympathetic, Trusting.
- Conscientiousness: Efficient, Organized, Planful, Reliable, Responsible.
- Neuroticism: Anxious, Self-pitying, Tense, Touchy, Unstable, Worrying.
- Openness: Artistic, Curious, Imagination, Insightful, Original, Wide interests.

The list above shows some examples for each personality of the BF. Each personality can be described with five scores showing how well the personality matches the words of each cluster. Decision of these scores is the goal of questionnaires

TABLE II
RELATED QUESTIONS CORRESPONDING TO EACH PERSONALITY

Personality Traits	Related Questions
Extraversion	1, 6R, 11, 16, 21R, 26, 31R.36
Agreeableness	2R, 7, 12R, 17, 22, 27R, 32, 37R, 42
Conscientiousness	3, 8R, 13, 18R, 23R, 28, 33, 38, 43R
Neuroticism	4, 9R, 14, 19, 24R, 29, 34R, 39
Openness	5, 10, 15, 20, 25, 30, 35R, 40, 41R, 44

TABLE III
THE BFI-10 QUESTIONNAIRE USED IN OUR EXPERIMENTS
(AS PROPOSED IN [13])

ID	Question
1	This person is reserved
2	This person is generally trusting
3	This person tends to be lazy
4	This person is relaxed, handles stress well
5	This person has few artistic interests
6	This person is outgoing, sociable
7	This person tends to find fault with others
8	This person does a thorough job
9	This person gets nervous easily
10	This person has an active imagination

such as the BFI which is commonly used in personality assessment.

B. Assessing Big Five Traits

There are several questionnaires for scoring personality traits according to the dimensions corresponding to the BF Model [13]. Table I shows the Big Five Inventory (BFI) with 44 items, the questionnaire adopted in this work. Each question in Table I is associated to a Likert scale including five points ranging from "*Strongly disagree*" to "*Strongly agree*" which maps to the interval from one to five. This scores corresponding to each personality traits can be obtained by summing up the scores from related questions. Table II shows the corresponding relation between questions and each personality where R indicates the items are reverse-scored (1 becomes 5, 2 becomes 4, 3 remains 3, 4 becomes 2, and 5 becomes 1). Moreover, the BFI has a simplified version with only 10 items which is called BFI-10. These 10 items listed in Table III are also included in the BFI full-item version. The main advantage of the BFI-10 is that it makes one to assess personality perception in a much shorter time than of the full BFI. The personality scores can be obtained using the answers provided by the assessors with a simple calculation (Q_i is the answer to item i):

- Extraversion: Q_6 — Q_1.
- Agreeableness: Q_2 — Q_7.
- Conscientiousness: Q_8 — Q_3.
- Neuroticism: Q_9 — Q_4.
- Openness: Q_{10} — Q_5.

However, given that the entire BFI consists of only 44 very short phrases and takes only 5 minutes to complete, in order to verify our proposed method. According to the original BFI authors, they do not recommend using the short 10-item version unless there are exceptional circumstances [13]. we adopted both versions of BFI for comparison in our experiments.

III. SPEAKER PERSONALITY PERCEPTION

The personality perception approach proposed in this paper includes three main steps: (i) extraction of low-level short-term acoustic-prosodic features from speech signal, (ii) detect the score for each of the items in BFI using an artificial neural network, and (iii) compute the final personality scores to predict the perception result.

A. Feature Extraction

In [2], the hypothesis of *"speech as a personality trait"* was proposed for the first time. Since that, a large number of studies have analyzed the effect of vocal behavior on personality perception. Up to the present, there are lots of acoustic-prosodic features have been investigated for personality prediction. In order to verify the proposed method quickly, we simplify the feature set for this work, and therefore the low-level descriptors (LLDs) are used.

The low-level features extracted in this paper includes the followings.

1. Zero-crossing rate
2. Root mean squared (RMS) frame energy
3. Pitch
4. Harmonics-to-noise ratio (HNR)
5. Mel-frequency cepstrum coefficients 1-12
6. Delta coefficient of the above features.

The reason behind the choice is not only that these features are the most important aspects of acoustic property and prosody, but also they are the most investigated cues about the relation between speech and affective perception.

The extraction has been performed with TUM's open-source openSMILE feature extractor [17], from 25 ms windows at a regular time step of 15ms. The low-level features are estimated at frame level thus they express the short term characteristics of vocal behavior.

B. Artificial Neural Network-based BFI detection

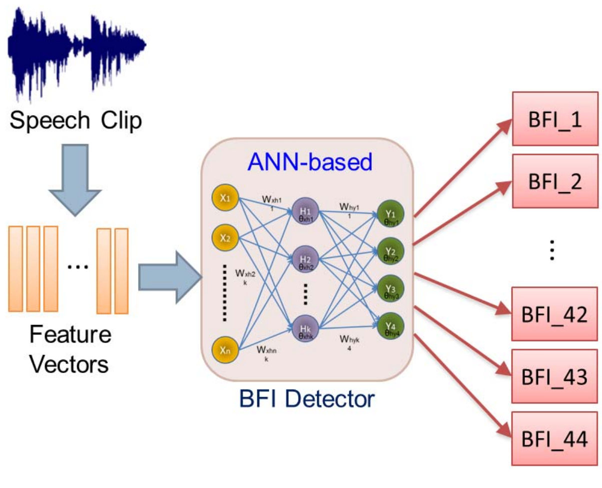

Fig. 2 ANN-based BFI Detector

In this work, the key component of the proposed approach is the Big Five Inventory (BFI) detector implemented using a feed-forward artificial neural network (ANN). Fig. 2 shows the basic concept of the ANN-based BFI detector. The goal of each BFI detector is to analyze the speech signal and produce a confidence score or a posterior probability that belong to some items in BFI. We build each detector using a feed-forward ANN with one hidden layer and 300 hidden nodes for 100 training iterations.

The ANN is trained by the classical back-propagation algorithm with cross entropy error function. The softmax activation function is used in the output layer, and the ANN produces the posterior probability that the BFI item happened during the frame being processed.

The inputs of all ANNs are the features we have extracted. The multiple outputs of ANNs are real values ranging from 0 to 1, which can be treated as the posterior probabilities of BFI items. The BFI item detection results which are used to compute personality score can be obtained by applying a decision process with a threshold 0.5. If the posterior probability is greater than 0.5, this BFI item is present, otherwise this item is absent.

C. Personality Scores Computing

As described in Section II, a personality perception assessment consists of 44 BFI scores which will then be used to obtain 5 continuous values corresponding to the Big Five Personality traits. To perform personality prediction, the assessment score of each BFI item is split into two classes, below (*Low*) or above (*High*) the average value. The former includes the samples that have a score lower than 3, while the latter includes the samples for which the score is higher than 3. The last step aims at assigning speech clips to one of the two classes (*High* or *Low*) associated with each personality trait.

According to Table II, each personality trait combines some corresponding BFI items for computing each final score. Supposing that the majority of BFI items corresponding to each personality is above the average, these personality traits are assigned to *High* class. On the contrary, the remaining personality traits are assigned to *Low* class. For the assessment on BFI-10, the rules we mentioned in Section II are used to obtain each personality score. Different from full BFI, each personality corresponds to two items for computing the scores. After the observation on BFI-10, we found that if the score is positive, this personality is assigned to *High* class, otherwise it is assigned to *Low* class.

IV. Experiments and Results

The goal of the proposed system is to predict the perceived personality according to the personality traits attributed to them by human assessors. This section describes the corpus we adopted in this paper and experimental results performed in our system.

A. The Data

The experiments of this study have been performed over the "Berlin Database of Emotional Speech" (EMO-DB) [18]. The corpus contains 535 German clips (about 130000 frames) recorded by 10 actors (5 female and 5 male) which could be used in everyday communication and are interpretable in general personality with emotions. Each clip includes only one speaker to avoid effects from conversational behavior on personality perception and the total duration of the corpus is around 20 minutes. The average length of the clips is around 3 seconds and do not contain words that might be easily understood by listeners who do not speak German. Because the assessors do not comprehend such a language, the personality trait assessments should be influenced particularly by nonverbal vocal behavior.

The personality trait assessments have been performed by 3 judges who have filled in the BFI-44 questionnaire for each of the clips in the corpus. The assessments have been done by asking the judges to fill in the questionnaire immediately after first listen to a clip. Consequently, a clip will be either in the *High* class assigned by the judge or in the *Low* class for a given trait and a given judge. This allows one to label the

TABLE IV
INSTANCES PER BFI IN OUR CORPUS

BFI item	Numbers of *High*/*Low* class	BFI item	Numbers of *High*/*Low* class
BFI_1	351/184	BFI_23	282/253
BFI_2	242/293	BFI_24	370/165
BFI_3	391/144	BFI_25	415/120
BFI_4	380/155	BFI_26	176/359
BFI_5	368/167	BFI_27	140/395
BFI_6	217/318	BFI_28	412/123
BFI_7	383/152	BFI_29	306/229
BFI_8	221/314	BFI_30	351/184
BFI_9	287/248	BFI_31	429/106
BFI_10	480/55	BFI_32	364/171
BFI_11	435/100	BFI_33	298/237
BFI_12	173/362	BFI_34	344/191
BFI_13	259/276	BFI_35	380/155
BFI_14	374/161	BFI_36	303/232
BFI_15	434/101	BFI_37	146/389
BFI_16	419/116	BFI_38	419/116
BFI_17	383/152	BFI_39	362/173
BFI_18	235/300	BFI_40	374/161
BFI_19	364/171	BFI_41	217/318
BFI_20	410/125	BFI_42	362/173
BFI_21	195/340	BFI_43	267/268
BFI_22	193/342	BFI_44	182/353

TABLE V
INSTANCES PER BFI-10 IN OUR CORPUS

BFI item	Numbers of *High*/*Low* class
BFI_1	217/318
BFI_2	193/342
BFI_3	282/253
BFI_4	287/248
BFI_5	217/318
BFI_6	303/232
BFI_7	242/293
BFI_8	391/144
BFI_9	362/173
BFI_10	410/125

TABLE VI
INSTANCE PER TRAIT IN OUR CORPUS BASED ON BFI

Personality Traits	Numbers of ***High*/*Low*** class
Extraversion	347/188
Agreeableness	262/273
Conscientiousness	377/158
Neuroticism	377/158
Openness	420/115
Total	1783/892

TABLE VII
INSTANCE PER TRAIT IN OUR CORPUS IN BASED ON BFI-10

Personality Traits	Numbers of ***High*/*Low*** class
Extraversion	338/197
Agreeableness	421/114
Conscientiousness	346/189
Neuroticism	350/185
Openness	290/245
Total	1745/930

clips as *High* or *Low* class for the majority of judges. As the number of judges is 3, the majority always includes at least 2 of them. Finally, each clip has been assigned to one class (*High* or *Low*) corresponding to each personality trait of the Big Five model. Table IV and Table V shows the number of *High* and *Low* class per BFI item in our corpus, and based on them, we can obtain the personality trait judges perceived by computing BFI scores. Table VI and Table VII shows the number of per trait in our corpus based on BFI and BFI-10.

B. Experimental Results

In our experiments we measure the effectiveness of the approach described in Section III to automatically predict whether a clip is in the *High* or *Low* class for each of personality traits. The experimental setup is based on the k-fold cross-validation method [19]: the entire dataset is divided into k equal-sized subsets; $k-1$ subsets are used for training and the remaining one for testing. The procedure is repeated k times and each time a different subset is left for testing; in the experiments of our work $k=5$. The folds have obtained with a random process and this allows one to test the approach over the entire corpus at disposition while keeping a rigorous separation between training and test sets. The performance is expressed in terms of accuracy, percentage of clips correctly classified in the test set. The overall accuracy is the average of the accuracies obtained over the k partitions mentioned above.

Fig. 3 reports the accuracy in detecting BFI items by using the ANN-based BFI detector we proposed in this paper. In this experiment, the BFI item accuracies of using ANN model and acoustic-prosodic features in detecting BFI items are presented. As shown in Fig. 3, the average BFI frame accuracy is 70% and the accuracy range of each items is from 60% to 80% for different items. Because some BFI items are difficult to be perceived from the nonverbal vocal behavior of speech, some items achieved especially high or low accuracy.

Similarly, Fig. 4 shows the result of ANN-based BFI-10 detector. The average BFI-10 frame accuracy is 71.56% and

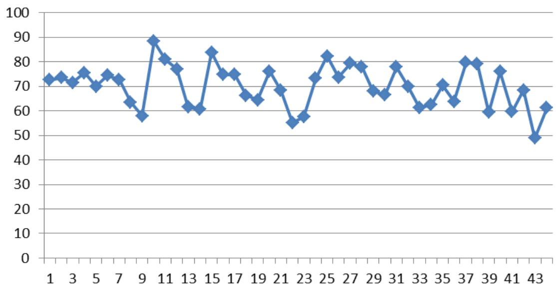

Fig. 3 Detection rate of ANN-based BFI Detector
x-axis: BFI number, y-axis: accuracy (%)

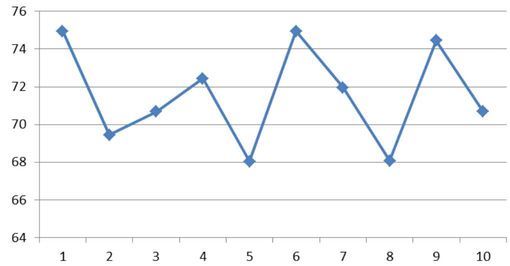

Fig. 4 Detection rate of ANN-based BFI-10 Detector
x-axis: BFI number, y-axis: accuracy (%)

the accuracy range of this ten items is from 68% to 75% depending on items. We can note that item 5 and item 8 are especially low than other items of BFI-10. It reveals the difficulty of some BFI items for personality perception from nonverbal vocal behavior of speech. The result show that the proposed ANN-based BFI detector can generally classify this BFI items from the clips in the frame level. In other words, we can obtain the BFI scores from speech signals automatically and then obtain the personality perception result through the BFI scores instead of obtaining the personality perception result directly from speech.

From the above results, we can conclude that the items of BFI are confusing. Some items can be perceived from speech but some cannot. As a result, either BFI or BFI-10 is not a satisfactory mechanism for representing the personality trait. We must consider each contribution of them and reach a better performance for personality perception.

Table VIII reports the accuracy obtained using ANN-based BFI detector to predict the perception of each personality trait at the sentence level. The average prediction rate achieved 69.85% higher than the frame-level ANN-based BFI detector. This indicates that the proposed BFI-based personality prediction can indeed utilize the ANN-based BFI detector to reach personality trait perception. For conscientiousness and openness, the accuracy under 70% appears to be lower than the others. A probable reason is that such traits are not so significant to affect the perception of listeners merely from the nonverbal vocal behavior.

In the same way, Table IX shows the accuracy of BFI-10-based personality perception system. Different from Table VIII, the results shows more effective performance than

TABLE VIII
PREDICTION RATE OF BFI-BASED SYSTEM (SENTENCE)

Personality Traits	Prediction Rate (%)
Extraversion	71.94
Agreeableness	72.41
Conscientiousness	66.49
Neuroticism	70.56
Openness	67.85
Average	69.85

TABLE IX
PREDICTION RATE OF BFI-10-BASED SYSTEM (SENTENCE)

Personality Traits	Prediction Rate (%)
Extraversion	73.86
Agreeableness	81.63
Conscientiousness	68.68
Neuroticism	72.46
Openness	70.27
Average	73.38

the BFI-based system. A probable reason is that different complexity between BFI and BFI-10 would lead to different results. BFI has more items than BFI-10 which can influence the personality perception results. Some items are difficult to be perceived in our experimental setting. Hence, using the BFI-based personality perception system must consider such noisy items which significantly affect the performance for personality perception.

V. CONCLUSIONS

This paper has presented a novel concept to predict personality trait by using the BFI for assessing the perception from listeners. In the experiments, we demonstrate the efficiency and effectiveness of the ANN-based BFI detector for personality trait detection. The experimental results of BFI-based speaker personality perception reveal that the proposed method achieved about 70% accuracy. The effectiveness of our ANN-based BFI detector for predicting personality perception is confirmed. In other words, it is possible to predict the personality perception of listeners from the detection of BFI. In our future work, we will consider more speech features and the relationship between BFI items to obtain better performance of BFI-based personality detector.

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