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Evaluation of Fuzzy and C_mean Clustering Methods used to Generate Voiceprint

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Abstract: Among biometric authentication methods, including fingerprint scanning, facial recognition and iris scanning, voice recognition ranked at the second-highest preference. In this paper we will introduce c_mean and fuzzy c_mean clustering methods. Different voice signals will be clusterized to get some features for each voice signal; it will be shown that using both methods we will get unique features for each voice signal, allowing us to identify a person and the spoken word.

Keywords: Voice signal, voiceprint, C_mean, fuzzy c_mean, cluster, centroid, speedup

1- Introduction

Acoustic biometrics is the technique used to identify a speaker through his / her voice characteristics. Each caller's voice provides unique audio features and behavioral features over the wire that can be analyzed in an invisible way to authenticate or identify the caller.

Identification examines the problem of identifying a speaker from a specific group of speakers. Typically two scenarios are considered: a closed group identification scenario in which the real speaker is one of the speakers known as N, and an open identification scenario where a real speaker can be one of the speakers who knows N or an unknown speaker. Open identification is usually a blacklisted fraud detection case.

Authentication, also known as verification, is the process of verifying the identity of the alleged person, which can be used to combat fraud.

A voiceprint is a set of measurable characteristic features of a human voice that uniquely identifies an individual person. These characteristics, such as length of the vocal tract, nasal passage, and pitch, cadence, accent, are based on the physical configuration of a speaker's mouth and throat, and they can be expressed as a mathematical formula, which allows us to use a voiceprints as a signature in voice ID systems for user authentication. Biometric technologies provide a foundation for identity support that makes the inherent biological and behavioral characteristics unique to each user, and provides a better user experience, customer experience, and accountability than other methods based on common credentials[1], [2].

The acoustic biometrics technology provides a higher level of safety than other solutions because biometrics relies on more than one physical property. Sound biometrics engines take into account sound behavior, what is being said, and countless audio features[3], [4]. These features are measured indirectly, given the data that is generated by the factors of how you speak, but are not exclusive to these physical properties. The information provided by these features is hidden by voice. The task of acoustic biometrics is to try to match recording samples that also contain that hidden information with experimental models containing the information. In addition, there are things that you can change around your voice and things that you cannot change[5], [6]. For example, you cannot change the length of the vocal paths, the basic frequency of your voice, etc., but you can change the pitch, accent, speed, and speed. These traits that you can change are what humans use to recognize and identify sounds, which also depend on inherent and insincere contributors [7], [8], [9].

The safety of voice recognition depends on several factors that we must ask:

Who has access to voice data?

How is the fingerprint controlled?

Is the audio fingerprint encoded? Is it encoded upon transmission?

Acoustic biometrics is the technique used to identify a speaker through his / her voice characteristics. Each caller's voice provides unique audio features and behavioral features over the wire that can be analyzed in an invisible way to authenticate or identify the caller. Acoustic biometrics can be further divided into other categories of speaker identification (SI) and speaker verification (SV). Speaker selection examines the language selection problem from a specific group, while language verification determines the identity of the speaker from his voice.

Authentication, also known as verification, is the process of verifying the identity of the alleged person, which can be used to combat fraud. It is a 1: 1 problem. For example, audio biometrics can be used as a method of validation, by checking the speaker's voice to confirm that the speaker is who they say. Due to the untouched nature of the speech, sonic biometrics has moved to the top of the comfortable biometrics list included in authentication [27-44].

On the other hand, voice recognition can be confusing, and the industry can refer to speaker recognition (such as vocal biometrics) or speech recognition[8].

Voice recognition is a major factor used in audio biometrics, and is usually in the form of a fingerprint program, which can then be used to authenticate the speaker. Voice tags can be taken negatively, while the speaker speaks freely or actively, while the speaker is instructed to pronounce a specific phrase. However, voice recognition is recognized by the print taken from the speaker's voice, and is independent of the speech used to create the voice tag [9]. The audio printouts used in audio biometrics are widely used within call centers to enhance authentication processes and provide an additional layer of security, figure 1 shows the process of voice recognition system:

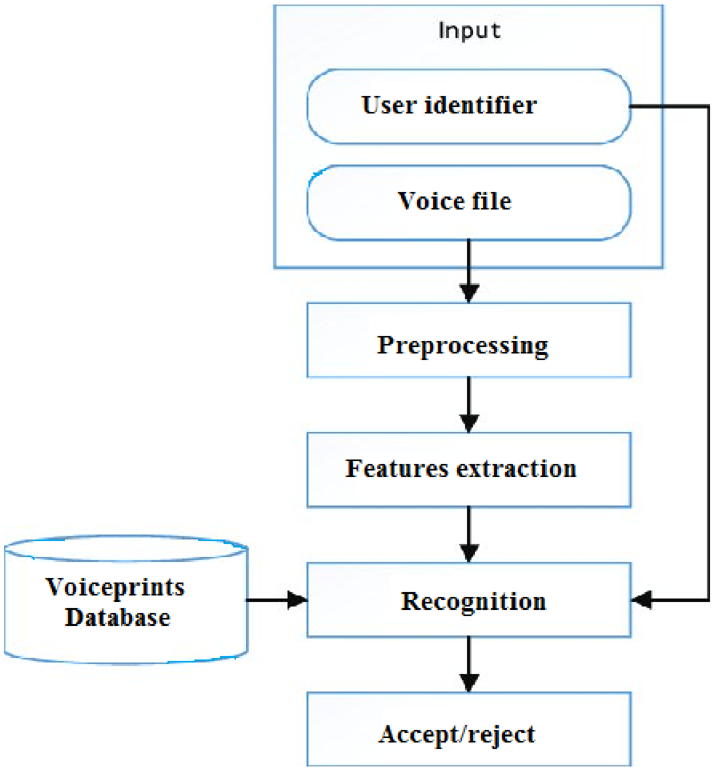

Figure 1: Voice recognition process

2- Voice signal clustering

The purposes of clustering methods is to obtain useful data by grouping the data elements in the input data set in clusters, within each cluster the data exhibits similarity[10]m [11], [12].

Digital voice signal as shown in figure 2 is represented by a set of amplitude values within a fixed range, these values can be grouped in clusters, and the clusters for each voice can for a voiceprint to identify the person and identify the spoken words[13]. [14].

Many methods [15],[16,[17] are used for data clustering, and here we will focus on the analysis of c_mean and fuzzy c_mean clustering. These two methods give use the ability to group the input data set into variable number of clusters[18], [19], these methods are also flexible, we can use the clusters centroids, or the within clusters sums to form the voice features, figure 3 shows how to group the input data into 4 clusters.

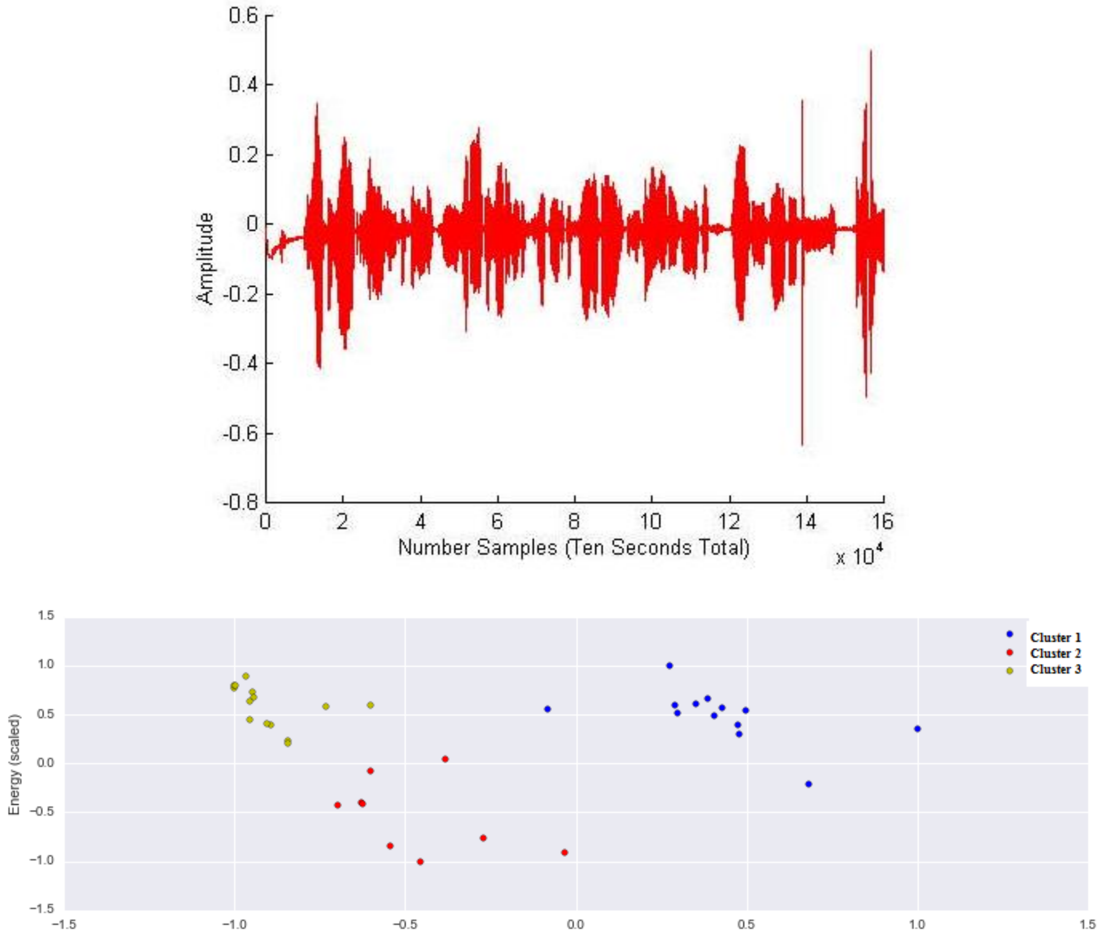

Figure 2: Clustering voice signal

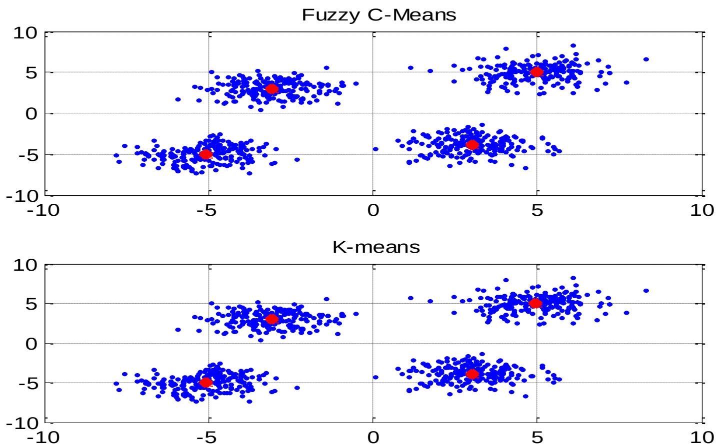

Figure 3: Grouping data into 4 clusters

Feature extraction is the most relevant portion of speaker recognition. Features of speech have a vital part in the segregation of a speaker from others [13]. Feature extraction reduces the magnitude of the speech signal devoid of causing any damage to the power of speech signal [14]. Feature extraction is the main part of the speech recognition system. It is considered as the heart of the system. The work of this is to extract those features from the input speech (signal) that help the system in identifying the speaker [20], [21].

The voice extracted features must satisfy the following [22], [23]:

- The extracted features must be small in size to minimize the memory space required to store these features, and minimize the architecture tool required for getting the voice classifier.
- The extracted features must be unique, thus they can be used to identify only one person.
- The extraction time must be significantly small.

3- Implementation and experimental results

We used 30 voice signals of adults with ages between 18 and 60 years. These signals were divided into six groups of people and each group was composed of 5 signals, which are recordings of sustained: zero, bye-bye, no, okay, yes.

Experiment 1: Extracting features for 5 words for the same person

Here we took the same person with 5 different spoken words, then we apply c_mean clustering for each voice signal, table 1 shows the results of this experiment:

Table 1: Experiment 1 results

Word	Features			
Zero	-0.1563	-0.0047	0.0967	0.2683
bye-bye	-0.2176	-0.0819	0.0103	0.1693
no	-0.1994	-0.0062	0.1067	0.2953
okay	-0.1663	-0.0067	0.0983	0.2467
yes	-0.4106	-0.0080	0.0388	0.4347

From table 1 we can see that each spoken word for the same person has unique features, so using these features we can identify the word or phrase spoken by a selected person.

Experiment 2: Extracting features for 1 word spoken by 6 different persons

Here we took the same word spoken by 6 persons, then we apply c_mean clustering for each voice signal, table 2 shows the results of this experiment:

Table 2: Experiment 2 results

Voice/person	Features			
Zero 1	-0.1563	-0.0047	0.0967	0.2683
Zero 2	-0.4999	-0.1812	0.0087	0.3699
Zero 3	-0.4701	-0.1831	0.0084	0.3268
Zero 4	-0.1662	-0.0051	0.1324	0.3262
Zero 5	-0.3337	-0.1018	0.0129	0.2225

From table 2 we can see that each spoken word for each person has unique features, so using these features we can identify the person.

Experiment 3: Evaluation c_mean and fuzzy c_mean clustering methods

Here we used 30 voice signals. These signals were divided into six groups of people and each group was composed of 5 signals, which are recordings of sustained: zero, bye-bye, no, okay, yes.

Tables 3 and 4 show the results of this experiment:

Table 3: Experiment 3 results(c_mean clustering)

Voice/person	Extraction time(s)	Features			
Zero 1	0.099000	-0.1563	-0.0047	0.0967	0.2683
Zero 2	0.132000	-0.4999	-0.1812	0.0087	0.3699
Zero 3	0.111000	-0.4701	-0.1831	0.0084	0.3268
Zero 4	0.111000	-0.1662	-0.0051	0.1324	0.3262
Zero 5	0.080000	-0.3337	-0.1018	0.0129	0.2225
Zero 6	0.081000	-0.2391	-0.0065	0.0979	0.3090
bye-bye 1	0.363000	-0.2176	-0.0819	0.0103	0.1693
bye-bye 2	0.308000	-0.1924	-0.0781	0.0051	0.1374
bye-bye 3	2.442000	-0.1198	-0.0069	0.0424	0.1638
bye-bye 4	0.621000	-0.1811	-0.0544	0.0136	0.1649

bye-bye 5	0.535000	-0.1742	-0.0076	0.0668	0.2260
bye-bye 6	0.498000	-0.0504	-0.0015	0.0455	0.1256
no 1	0.174000	-0.1994	-0.0062	0.1067	0.2953
no 2	0.271000	-0.1168	-0.0463	0.0107	0.1391
no 3	0.622000	-0.2967	-0.1058	0.0107	0.2719
no 4	0.592000	-0.1254	-0.0356	0.0059	0.1401
no 5	0.557000	-0.1680	-0.0605	0.0132	0.1802
no 6	0.873000	-0.1566	-0.0248	0.0027	0.0361
okay 1	0.269000	-0.1663	-0.0067	0.0983	0.2467
okay 2	0.999000	-0.1529	-0.0053	0.0708	0.2197
okay 3	1.522000	-0.1323	-0.0074	0.0578	0.2104
okay 4	0.386000	-0.1110	-0.0058	0.0554	0.1542
okay 5	0.463000	-0.0719	-0.0020	0.0652	0.1740
okay 6	1.069000	-0.0866	-0.0282	0.0062	0.1088
yes 1	0.245000	-0.4106	-0.0080	0.0388	0.4347
yes 2	0.190000	-0.0641	-0.0032	0.0333	0.0932
yes 3	0.456000	-0.1365	-0.0469	0.0044	0.1593
yes 4	0.624000	-0.1392	-0.0048	0.0783	0.2534
yes 5	0.291000	-0.0382	-0.0019	0.0212	0.0624
yes 6	0.460000	-0.1306	-0.0061	0.0739	0.2095
	0.5148				

Table 4: Experiment 3 results(fuzzy c_mean clustering)

Voice/person	Extraction time(s)	Features			
Zero 1	0.919000	-0.1543	-0.0027	0.0883	0.2602
Zero 2	0.934000	-0.4327	-0.0095	0.1253	0.4161
Zero 3	1.422000	-0.4010	-0.0040	0.1339	0.4370
Zero 4	0.458000	-0.2493	-0.0863	0.0054	0.2145
Zero 5	0.928000	-0.3412	-0.0978	0.0087	0.2202
Zero 6	1.025000	-0.3078	-0.0867	0.0036	0.2199
bye-bye 1	2.740000	-0.2022	-0.0722	0.0083	0.1680
bye-bye 2	4.356000	-0.1253	-0.0047	0.0678	0.1802
bye-bye 3	35.047000	-0.1391	-0.0326	0.0063	0.1112
bye-bye 4	8.310000	-0.0998	-0.0036	0.0561	0.2207
bye-bye 5	11.490000	-0.1615	-0.0069	0.0469	0.1979
bye-bye 6	5.480000	-0.0480	-0.0015	0.0385	0.1072
no 1	3.066000	-0.2729	-0.0920	0.0055	0.2212
no 2	3.398000	-0.0959	-0.0030	0.0702	0.1873
no 3	9.039000	-0.2705	-0.0847	0.0075	0.2572
no 4	6.751000	-0.0576	-0.0012	0.0317	0.1645
no 5	3.635000	-0.1598	-0.0545	0.0089	0.1679
no 6	10.552000	-0.0270	-0.0016	0.0173	0.0359
okay 1	3.518000	-0.2007	-0.0698	0.0066	0.1826
okay 2	14.197000	-0.1906	-0.0462	0.0049	0.1308
okay 3	24.342000	-0.1158	-0.0053	0.0494	0.2040
okay 4	5.639000	-0.1782	-0.0582	0.0034	0.1071
okay 5	5.159000	-0.0686	-0.0017	0.0605	0.1676
okay 6	9.517000	-0.0646	-0.0022	0.0375	0.1304
yes 1	3.352000	-0.4636	-0.0081	0.0242	0.4671
yes 2	3.751000	-0.0820	-0.0277	0.0026	0.0643
yes 3	8.142000	-0.1034	-0.0027	0.0444	0.1869
yes 4	6.991000	-0.1399	-0.0394	0.0050	0.1694
yes 5	3.508000	-0.0491	-0.0170	0.0015	0.0363
yes 6	4.322000	-0.1297	-0.0041	0.0698	0.2053
	6.7329				

From tables 3 and 4 we can see the following important points:

- Both c_mean and fuzzy c_mean methods of clustering gave unique features for word/person voice file.
- Using the two methods of clustering we can identify the person and the spoken word, thus we can use the voiceprint as a password in a security system.
- The features obtained by c_mean clustering methods are not similar to those obtained by fuzzy c_mean clustering method, but they are unique.

- C_mean clustering method is more efficient than fuzzy c_mean clustering method, requiring less time for features extraction and has a speedup of 13.0787(6.7329/0.5148).
- It is very easy to pass the features to a recognition tool such as artificial neural network (ANN) [24], [25], [26], this tool will use the features to find the classifier for both the person and the spoken word , figure 4 shows a sample of the input data set and the targets for ANN:

INPUT	-0.1563	-0.4999	-0.4701	-0.1662	-0.3337
	-0.0047	-0.1812	-0.1831	-0.0051	-0.1018
	0.0967	0.0087	0.0084	0.1324	0.0129
	0.2683	0.3699	0.3268	0.3262	0.2225
OUTPUT	**1**	**1**	**1**	**1**	**1**
	1	**2**	**3**	**4**	**5**

Figure 4: Input sample for ANN

Experiment 4: Using 6 clusters

The voice signals for the word "Okay" spoken by 6 different persons were taken and Clusterized, table 5 shows the results of this experiment:

Table 5: Experiment 4 results

Voice	Clustering	Features						Extraction time(s)
Okay-1	c-mean	-0.2553	-0.1478	-0.0606	0.0043	0.1113	0.2568	0.611000
	Fuzzy	-0.2118	-0.0890	-0.0017	0.0624	0.1602	0.2877	8.644000
	c-mean	-0.2670	-0.1237	-0.0394	0.0039	0.0825	0.2314	1.839000
Okay-2	Fuzzy	-0.2552	-0.1085	-0.0294	0.0038	0.0779	0.2226	26.190000
	c-mean	-0.2298	-0.1059	-0.0378	0.0036	0.0721	0.2211	3.349000
Okay-3	Fuzzy	-0.1872	-0.0604	-0.0019	0.0409	0.1277	0.2651	52.861000
	c-mean	-0.1988	-0.0715	-0.0038	0.0366	0.0938	0.1798	0.602000
Okay-4	Fuzzy	-0.1929	-0.0690	-0.0027	0.0327	0.0896	0.1756	5.768000
	c-mean	-0.1139	-0.0470	-0.0012	0.0415	0.1025	0.2036	0.950000
Okay-5	Fuzzy	-0.1206	-0.0604	-0.0241	0.0019	0.0693	0.1749	9.313000
Okay-6	c-mean	-0.0943	-0.0382	-0.0008	0.0355	0.1036	0.2471	1.457000
	Fuzzy	-0.0866	-0.0340	-0.0004	0.0328	0.0973	0.2393	22.391000
Average Speedup=14.2106 times(c-mean efficiency in 14.2106 times higher than fuzzy efficiency)								Average=1.4680 Average=20.8612

Here we can see that the features are unique, but the required extraction time is bigger, and the speedup of c_mean clustering compared with fuzzy clustering is in average 14.21 times.

Conclusion

Different voice signals using different spoken words by different persons were clusterized by c_mean and fuzzy c_mean methods and the obtained experimental results showed the following facts:

- The extracted features for each person were unique.
- The extracted features for each word-person also were unique.
- Using the extracted feature we can identify both the person and the spoken word.
- C_mean clustering is more efficient and has a speed up of 14 comparing with fuzzy c_mean clustering.

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