THE DEVELOPMENT OF TEXT-INDEPENDENT SPEAKER RECOGNITION TECHNOLOGY

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Abstract: *Speaker recognition has been used for thousands of years to authenticate the identity of a person. During the last five decades modern technology developments and modern mathematical techniques have been applied to speaker recognition. These modern advancements have allowed for the creation of autonomous speaker recognition systems. This paper surveys the history of text-independent speaker recognition and the advances in related sciences which have allowed autonomous speaker recognition systems to become a practical means of identity authentication.*

Key words: *Speaker Recognition, Biometric, identity authentication, text independence*

1. Introduction

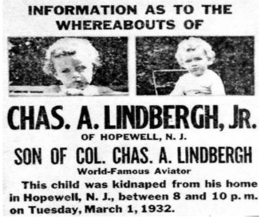
Speaker recognition is the biometric of voice. A speaker recognition system measures the attributes of a person's voice or speech in order to make a judgment concerning that person's identity. Human beings perform this task on a regular basis. For instance, recognizing a relative or a close friend's voice without other means of identification is often done over the phone. Autonomous speaker recognition systems measure attributes of a person's voice or speech and makes judgments regarding that person's identity through electronic devices. Autonomous speaker recognition systems have made major advances throughout the last five decades. Today's systems provide a practical means of verifying user access rights, identifying personnel in a group and even limited use in forensic applications.

The earliest research in speaker recognition was in the realm of human abilities. Later war time research allowed for significant advances in autonomous systems, producing a tool to allow visual inspection of voice. Advances in signal processing techniques and the rise of the computer permitted true autonomous systems to be developed. Limitations to these systems include voice-capture system mismatch, dependence on known texts, noise, channel effects and others. Despite these limitations, some applications have made sufficient advances to make commercial systems a reality. This Article is a review of the progress of speaker recognition systems. The article illustrates how recognition systems have advanced throughout the years and identifies current and future research trends in this field.

2. Early beginnings – Earwitnesses

The problem of recognizing an individual by their voice is an age old issue. Genesis records Isaac's dilemma in verifying a speaker when Jacob acts as an imposter of his brother Esau. Isaac's confusion was with two contradictory biometrics. "The voice is Jacob's voice, but the hands are the hands of Esau." Jacob trusted tactility over auditory "and he discerned him not." (Gen. 27:22-23) The speaker recognition problem arose throughout history and even appears in a judicial case as early as 1660 [1]. A couple of centuries later, academic research would begin investigating voice biometrics.

In March of 1932, Charles and Anne Lindbergh's baby boy was abducted and subsequently killed. The investigation led to a clandestine payoff in a cemetery where a Lindbergh operative met with an anonymous male claiming to be the kidnapper. Charles Lindbergh sat in a nearby car. Lindbergh overheard the anonymous man say "Hey Doctor, over here, over here". This was the second time Charles Lindbergh had heard this man's voice without seeing his face. Two and a half years later at the trial of the accused kidnapper, Bruno Hauptmann, Lindbergh claimed to be able to identify Hauptmann's voice as the same voice heard in the cemetery [1].



WANTED
INFORMATION AS TO THE WHEREABOUTS OF
CHAS. A. LINDBERGH, JR.
OF HOPEWELL, N. J.
SON OF COL. CHAS. A. LINDBERGH
World-Famous Aviator
This child was kidnaped from his home in Hopewell, N. J., between 8 and 10 p. m. on Tuesday, March 1, 1932.

Fig. 1 – Lindbergh wanted poster

The Lindbergh case spurred Frances McGehee to initiate the first documented academic research on the reliability of earwitnesses. Her research led to the publication of two significant articles on the topic The Reliability of the Identification of the Human Voice and An Experimental Study Voice Recognition [2-3]. Since McGehee, research into speaker recognition has been a consistent topic in forensics and psychology research. The later development of the autonomous speaker recognition system has its roots in the work of McGehee.

3. The first speaker recognition system

It was in 1962 that an article was published in Nature by a Bell Laboratories Physicist Lawrence G. Kersta entitled, "Voiceprint Identification" [4]. Two years previous, Bell Laboratories had been approached by law enforcement agencies about the possibility of identifying callers who had made several verbal bomb threats over telephone lines [5]. The task was given to Kersta. After the two years of research he claimed he had a method to identify individuals with very high success rates. His method utilized earlier work on speaker recognition performed by three other Bell Laboratories' scientists, Potter, Kopp and Green who were working on voice identification for military applications during World War II [6]. They had developed a visual representation of speech called a spectrogram. A spectrogram records the frequency and intensity of a speech signal with respect to time. Kersta's claims of identifying speech via spectrograms sparked several research projects over the next year. In fact, his article sparked an entire field of research. There were several dissenting views in the next few years. Researchers were unable to replicate the results of Kersta's work.

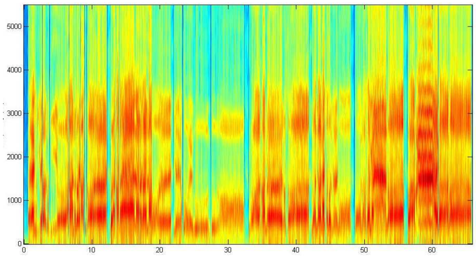


Fig. 2 - Sample Spectrogram

To help settle the matter, a substantial research project was undertaken by Oscar Tosi, a professor at Michigan State University who had initial doubts about Kersta's "voiceprint". In conjunction with the Michigan State Police and sponsored by the Federal Department of Justice, Tosi's research actually yielded promising results [7]. Tosi's results tended to support Kersta and lent validity to the field.

Tosi's research was not without critics. One year after Tosi's research was published, his results were refuted by MIT scientist and co-founder of the BBN consulting firm, Richard H. Bolt. Bolt's team illustrated holes in the Tosi experimental methodology [8, 9]. Tosi's experiment lacked scientific basis in practical applications. The FBI, being interested in the forensic application of speaker identification, requested another study be performed by the National Academy of Sciences. The results from this study showed that the technical uncertainties in forensic applications were substantial enough to claim the use of voiceprints were unreliable in any useful application. However, voiceprints are still found useful in certain circumstances. In fact the FBI has utilized a form of Kersta's spectrogram analysis as late as 2002 [5].

The Kersta method is an aural-visual method. From a voice sample a spectrogram is produced. This spectrogram is then inspected visually for pattern matching and scored by the interpreter. Success rates with this method, given an expert interpreter and proper environmental circumstances, can be very high. Despite this success, it requires human interaction, limiting its use in security applications. Also, "the good performance reported in Kersta's paper has not been observed in subsequent evaluations simulating real-life conditions" [10].

Though this method is still utilized in some forensic applications, such as with the FBI, it has not materialized into a practical speaker recognition system. The human factor of the spectrogram system limits its range of applications. For use in automated identity verification, recognition systems would need to be autonomous, and for most applications have low error rates. Computing techniques have since been employed allowing for autonomous, low computing costs, low error rate systems.

4. Behind automatic recognition systems

It was in the 1960's when several developments made autonomous speaker recognition possible. These developments covered a broad range of disciplines and for the most part were independent of speaker recognition research. For instance, Gunnar Fant produced a physiological model of human speech production in 1960 [11]. The Fant model and similar research that followed, became the basis for understanding how to analyze speech for both speaker recognition as well as automatic speech recognition. Research into the physiological aspects of voice led future researchers to represent voice as a linear source-filter type model. Understanding voice using such a model allowed for many advances in discovering identifiable characteristics in an individual's voice.

As computers became more accessible to more scientists, problems of implementation of continuous-domain mathematical solutions in a discrete world arose more and more often. These issues were critical to the field of digital signal processing. In 1965 Cooley and Tukey published their method of digital implementation for the Fourier transform. It is now known as the Cooley-Tukey Fast Fourier Transform (FFT) [12]. The FFT gave scientists an efficient method of frequency analysis in computer based systems. It was a major advance and it coincided with other investigations at the time. Two years earlier in 1963 Bogert, Healy and Tukey had published a study on echo detection in seismic signals titled "The Quefrency Alanysis of the Time Series for Echos: Cepstrum, Pseudo-Auto-Covariance, Cross-Cepstrum, and Saphe Cracking" [13]. This oddly titled paper described a method of echo detection by taking the "spectrum" of a log-magnitude spectrum. Inspired by the echo-detecting Cepstrum, Michael Noll explored the use of the Cepstrum for pitch detection of a human voice [14]. During the same period, Alan Oppenheim's research into homomorphic signal separation, led to him defining the Complex Cepstrum, which is the complex-valued Fourier transform of the log spectrum [15]. Ronald Schafer soon joined Oppenheim research efforts. Oppenheim and Schafer, building on Noll's pitch detection, used cepstral analysis to model speech [16, 17]. The Cepstral speech model became an important tool for speaker recognition systems.

In another completely unrelated study in the late 1960's Leonard E. Baum and others developed a stochastic model for Markov processes. The process attempts to determine hidden parameters of a statistical model from observable features in the model and is called the Hidden Markov Model (HMM) [18]. Though this statistical model would find broader application in the parallel studies of speech recognition, it would also play a limited role in speaker recognition as well. The fortuitous computer, mathematical and physiological developments of the 1960's laid the foundation for modern speaker recognition systems.

5. Early autonomous systems

During the 1960's several investigations into automatic speaker recognition systems began. For instance, Pruzansky a Bell Laboratories Engineer investigated early systems for automatic speaker recognition utilizing spectral pattern matching techniques [19, 20]. This system had a measure of success. However, the first successfully implemented autonomous speaker recognition system was a multimodal system which utilized voice and signature analysis. It was developed by a team led by George Doddington at Texas Instruments in 1977 [10, 20, 21]. This system used digital filter banks to do spectral analysis. It was a text-dependent system that prompts the user for the correct verification phrase. The output vector of a 14-channel filter bank is used in a 'Euclidian distance' based algorithm to make a verification decision. Over many years, this system had a false rejection rate of less than 1% and a false acceptance rate of less than 1% [10].

The early recognition features used as measures included spectral resonance, filter banks vectors and linear predictive coefficients. Utilizing these features produced a good level of success in text-dependent systems. The early systems which did have success were all text-dependent. Later research has been able to improve on those early text-dependent successes. Investigations into text-independent methods since those early days have continued. This research differs from the text-dependent research as scientists look for underlying indentifying attributes, as opposed to spectral pattern matching or phonetic event measurements. This research also trends toward speaker identification, as opposed to the simpler task of verification. To generate a practical text-independent system, further research was required.

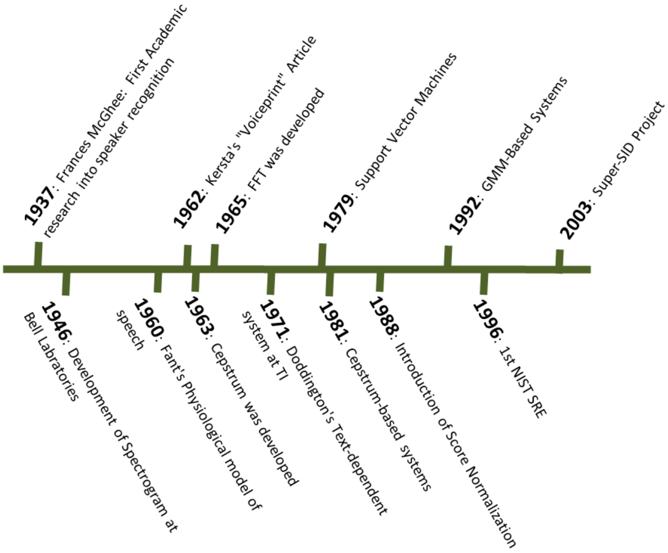

1937: Frances McGhee: First Academic research into speaker recognition
1946: Development of Spectrogram at Bell Labratories
1960: Fant's Physiological model of speech
1962: Kersta's "Voiceprint" Article
1963: Cepstrum was developed
1965: FFT was developed
1971: Doddington's Text-dependent system at TI
1979: Support Vector Machines
1981: Cepstrum-based systems
1988: Introduction of Score Normalization
1992: GMM-Based Systems
1996: 1st NIST SRE
2003: Super-SID Project

Figure 3 - Timeline of Major Speaker Recognition Events

In 1969 James Luck, building on Schafer and Oppenheim's model, proposed that the brainchild of Bogert and company, the cepstrum, be applied to speaker recognition [22-24]. It took some time before Luck's concept of cepstrum-based speaker recognition became widely used. The results of a study at Bell Laboratories were published by Bishnu Atal in 1974 [25]. The results demonstrated a marked improvement in identification accuracy of the cepstral approach over other approaches. Nevertheless, many researchers during the decade following Luck's publication overlooked cepstral-based systems. Many systems of this era focused on text-dependent systems using spectral features of voice. Such features included fundamental frequency analysis, spectral template matching, and time averaged spectral characteristics. In 1981 Sadaoki Furui published results of another Bell Laboratory study [26]. The publication described the use of the cepstral coefficients and their orthogonal polynomial coefficients in a frame-based system. The system was tested extensively. The success of the project sparked a renewed research effort on the use of the cepstrum in text-independent systems. The Cepstral approach uses the homomorphic deconvolution capabilities of the Cepstrum to separate the vocal tract envelope from the glottal excitation component of speech. It is the ability to analyze the de-convoluted voice signal that makes cepstral analysis a powerful tool in speaker recognition. The Cepstral approach has dominated voice feature selection in text-independent research for the last three decades [23, 24, 27]. Though some of today's research supplements these features with other high level speech features, cepstral analysis still plays a dominant role in speaker recognition.

As important to an accurate recognition system as feature selection/extraction is, the modeling and decision making algorithms are equally important. This field of study has also made significant improvement from the simple Euclidian distance method found in the TI system. The Hidden Markov Model, developed in the late 1960's, was employed widely in speech and speaker recognition systems during the 1980's. Also a method of vector quantization (VQ), compressing a speaker feature vectors down to a small set, was also studied. However, the research of Matsui and Furui showed that with enough training data the HMM and the VQ was about as effective as the less computationally demanding Gaussian Mixture Model (GMM) [8, 21, 28]. The VQ method lived a short life and is no longer a serious approach to state-of-the-art speaker recognition. Though the HMM is the standard method for speech recognition, and is utilized in text-dependent speaker recognition systems, it is found less often in modern text-independent speaker recognition.

6. Advances in autonomous recognition systems

Each basic section of the recognition system, such as feature selection/extraction, feature modeling, feature classification and decision making, has made significant enhancements in the last fifteen years. Many advances, such as score normalization, have been made to overcome lingering obstacles, such as intrapersonal variations, environmental noise and equipment mismatches. The advances in each of the various sections of speaker recognition systems have helped turn speaker recognition from solely a scholarly activity to a limited commercial reality. The remainder of this section reviews a few of the modern advances in speaker recognition.

A. High Level Features.

The Mel-Frequency Cepstrum Coefficients or other variants of low level, short term (10-20ms) voice features has long been the preferred feature for most speaker recognition tasks. Utilizing low level features has been productive. However, the low-level approach ignores other identifiable information in a person's speech. The low-level features measure attributes of a person's voice (example: Pitch). The high level features measure attributes of a person's speech (example: length of pauses between words). The idea that high-level features carried useful information in recognition systems was known for many years [25]. Early investigations tried to capitalize on this by using long-term averages of speech features.

These early attempts had limited success. With the advent of the short-term cepstrum the emphasis in research reverted back to low-level analysis. Serious investigations related to higher level features for autonomous speaker recognition began to appear around the turn of the century [29]. One notable project, sponsored by NSF and the department of defense, (the Super-SID project) gathered prominent scientists in the field to test the idea of using high level features. The Super-SID project demonstrated a marked improvement when utilizing a fusion of both high and low level features [30].

B. The GMM-UBM

Throughout the years, several types of feature modeling have been used. These include the Hidden Markov Model, Vector Quantization, nearest neighbor and template matching models. In 1992, a recently graduated PhD student, Douglas Reynolds joined the Information Systems Technology group at MIT's Lincoln Laboratories. Reynolds Doctoral work had centered on modeling voice features for speaker recognition with Gaussian mixture models. His work led to a new paradigm in speaker recognition. [31-33].

The GMM performs similarly or better than other modeling techniques with a significant reduction in computational resources. By itself, the GMM marks a significant improvement in recognition systems. However, the simple multivariate Gaussian mixture models have been improved upon in several respects. One improvement, and perhaps the most notable, was the addition of the Universal Background Model (UBM). The UBM was another brainchild of Reynolds [33]. In addition to modeling a person's voice and testing the likelihood of that person being the authenticated user, it was proposed to use a set of people who were not the authenticated user. This allowed Bayesian theory to be employed and likelihood ratios used. The utterances given from a set of non-authenticated users are used to train a single GMM (GMM-UBM) with a large number of mixtures. The test utterance provided at time of authentication is not only tested against the user's trained GMM but also against the GMM-UBM. The GMM-UBM is used to represent a speaker-independent distribution of features for that particular system. Therefore, the closer a user's test utterance matches the authenticated training data and the less it matches the UBM, the more likely that user is an authenticated user. The innovation of employing a single GMM as opposed to a set of GMM's trained by individuals marked a significant advance in speaker recognition.

C. MAP-Adaptation and Supervectors

The GMM-UBM was further enhanced by training the speaker model using adaptation. A group of scientists, again led by Reynolds at the Lincoln Laboratories used a form of Bayesian learning called maximum a posteriori (MAP) estimation to provide this adaptation [34, 35]. The basic idea of adaptation is to derive the speaker model using the highly-defined UBM statistics in conjunction with the feature vectors from the speaker's training utterance. Instead of modeling the speaker's voice, adaptation models the speaker's variance from the GMM-UBM. The major advantage of the MAP-adapted GMM is that during authentication of a non-imposter when testing features do not align with the trained model, but do with align with "universal" features, then the negative affect of those features on the likelihood score will be mitigated.

Supervectors in the context of speaker recognition are the concatenation of the mean of each element in a multivariate MAP-GMM. The idea of the supervector had been applied to use in HMM's for speech recognition applications during the 1980's (for example [36]). During the 1990's scientists made some attempts to apply similar supervector concepts to speaker recognition. It was after the development of the GMM-UBM and MAP adaptation that supervectors really became useful for modern speaker recognition. The modern use of supervectors used in conjunction with the MAP-GMM helped commence much innovation with respect to classification techniques, which constitutes a sizable portion of the current research in speaker recognition.

D. Support Vector Machines

Support Vector Machines (SVM) are used to classify data. In the verification task, the SVM is used to classified data as an authenticated user or an imposter. The advantage of the SVM classifier is that it is able to minimize false reject and false accept error rates by using an optimized non-linear decision boundary (as opposed to a simple threshold).

SVM's were first developed in 1979 by a Russian statistician Vladimir Vapnik. Vapnik published the basic concepts of SVMs in Estimation of Dependences Based on Empirical Data [37]. In the 1990's SVMs were applied to machine recognized, hand-written digits [38]. The successful use in recognizing handwriting helped inspire the idea of using SVM in speaker recognition. In 1996, Michael Schmidt and Herbert Gish, both with BBN Systems and Technologies, reported on the first attempt at applying SVMs to speaker recognition [39].

The first attempt at implementing SVM in speaker recognition systems did not demonstrate a real improvement over other conventional methods [31]. However, that first attempt combined with SVM advances in other applications, spurred on further research. Over the decade following Schmidt and Gish's publication, the SVM method became an important element of speaker recognition research [40].

E. Score Normalization

One substantial enhancement which has made practical recognition systems a reality is score normalization. Like SVMs, score normalizations are designed to mitigate decision errors. The SVM technique attempts to minimize error by altering the decision boundary. Score normalization attempts to minimize error by altering the scoring, and thus moving speaker model vectors away from the decision boundary.

Score normalization research largely began with Li and Porter's proposal in 1988 to normalize the score distribution of the imposter model [8, 41]. This first attempt led to many different variations of score normalization. For instance, the zero normalization or Znorm is a method to perform normalization during the enrollment period. The test normalization or Tnorm is similar to the Znorm in purpose. The Tnorm however, is performed during the testing phase [8]. The Hnorm and the HTnorm normalization presented a way to mitigate errors resulting from handset mismatched conditions, a major issue in providing real world solutions [42]. Score normalization has made a marked improvement in error rates. Score normalization continued to be a focus of research over the decade following Li and Porter's research. Research has trailed off somewhat in relation to score normalization, mainly due to the focus on other pattern classification techniques. However, limited score normalization research continues today[43, 44]. The better data can be classified, the better a system's ability to properly verify and properly reject persons attempting authentication.

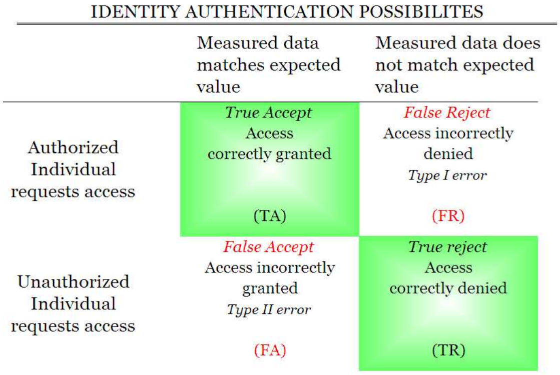
F. NIST SRE

The ability to quantify performance of any general system can sometimes be difficult. Measuring the performance of an automobile for instance is not straight forward. One may define performance as horsepower where another may define performance as fuel efficiency. Even if it is determined that fuel efficiency is the metric for performance, how that metric is measured can differ from automaker to automaker. A set standard assists in making an apple to apple comparison of a system. In 1996 the National Institute of Standards and Technology (NIST) began performing system evaluations for text-independent speaker recognition systems [45].

In the mid-1980's standard speech corpora were developed to standardize speaker recognition system testing. In the early 1990's the "Switchboard-1 Corpora" was collected by Texas Instruments for DARPA. The Speaker Recognition Evaluation (SRE) performed by NIST in 1996 used this Corpus [46]. Over the years, additional corpora were developed to assist in further research of specific topics. For instance, in 1999 a switchboard corpus utilizing the growing GSM cellular technology was used in the NIST SRE. The following year a different corpus was used with CDMA cellular technology [46]. As the research and testing continues, the Corpuses utilized in evaluations have also changed. This has assisted in researchers developing new technology to overcome specific problems. However, altering the corpus every year or two makes it difficult to track the real improvement of the technology over the years.

Table 1

IDENTITY AUTHENTICATION POSSIBILITES



	Measured data matches expected value	Measured data does not match expected value
Authorized Individual requests access	*True Accept* Access correctly granted (TA)	*False Reject* Access incorrectly denied *Type I error* (FR)
Unauthorized Individual requests access	*False Accept* Access incorrectly granted *Type II error* (FA)	*True reject* Access correctly denied (TR)

NIST SRE defines its performance measure as a decision cost function. The function uses the weighted probability of a falsely reject user and the weighted probability of a falsely accepted imposter. The results are reported in Detection Error Tradeoff (DET) curves. Participants in the NIST evaluations have become a global group, expanding to 58 participants from 5 continents (SRE 2010) [47].

7. Current trends and future research

Commercial text-independent speaker recognition systems exist today. Commercial systems perform with low enough error rates to make them practical in many applications. In the 2010 NIST SRE, equal error rates for the best systems were below 2% for core conditions [47]. Though a 2% equal error rate is sufficient for many applications, many applications have much more stringent requirements. Much research effort today is placed into reducing this error rate.

Speaker recognition is a subset of the larger field of pattern recognition. In the last several years the broader field of pattern recognition techniques has contributed a lot to speaker recognition research. Currently joint factor analysis plays a major role in many high performance recognition systems [48-50]. Principal component analysis, linear discriminant analysis, latent factor analysis and many other techniques for dealing with classification in stochastic data have also been applied to speaker recognition systems [40, 48, 51-53]. These techniques are offspring of the application of supervectors to speaker recognition [40, 54]. The use of classification techniques in the supervector's high-dimensional space intends to mitigate the effects of inter-speaker differences, inter-session variance, or equipment variation. Application of pattern classification advances to speaker recognition will continue to be a strong field of research.

As discussed above, it was discovered that the fusion scores from high-level speech features with traditional low-level features was one method that has helped lower error rates. The disadvantage of the fused system is the computational cost. Fused systems are still looked at today. However, the mathematical techniques of pattern recognition applied to speaker recognition has reduced error rates a significant amount and reduced the computational cost of the overall systems enough that fused systems using high-level features appears to currently be impractical for real-world systems [48].

Improving error rates will continue to be a major emphasis of research. One major application requiring much improved error rates is identification purposes in forensic applications. Currently caution is required for forensic uses of speaker identification [55]. A minimal EER rate in text-independent systems would give forensic scientists the ability to use speaker recognition in the same manner they use DNA evidence.

The push toward forensics has opened up some interesting basic research. For instance, performing research to better understand what voice features are common among speakers has recently been undertaken [56, 57]. This research will surely lead to further research into which vocal features change depending on age, ethnicity, language, emotion, intent, dialect region or other factors. Another interesting topic of research which has been promulgated for forensic purposes reaches back to the beginning of autonomous speaker recognition. In 2010 the NIST SRE included a Human Assisted Speaker Recognition (HASR) test [58]. Similar to the idea of the Kersta's voiceprint, HASR attempts to lower error rates by allowing humans (research has been done on both trained and untrained individuals) to supplement the autonomous systems. Early research demonstrates a possibility for further advancement in this field [59].

The human assisted methods are motivated by the fact that the low error rates obtained with modern speaker recognition are still higher than speaker recognition as performed by humans. Future advances in the autonomous speaker recognition systems then may lie in a better understanding of the way humans identify speakers.

Of course a major area of research continues to be environmental variability, such as background noise or handset variability [60-62]. Environmental concerns become a major factor in applications where unknown conditions exist. With the advent of the internet and security applications over the internet, such as internet banking, security needs in unknown conditions have become more and more prevalent. Therefore, research into environmental concerns will continue to be a focus in speaker recognition systems research.

8. Summary and conclusion

The use of voice as a biometric spans centuries of time. In the early part of the twentieth century, vocal recognition began to be studied as a serious academic venture. Combining the idea of speaker recognition with the rise of the computer has led to the autonomous speaker recognition system.

It was in the very early years of computing that the idea of computer-based voice recognition was proposed. The invention of the spectrogram during World War II was the first step toward a computer-based recognition system. Kersta's research in the 1960's on "voiceprints" built on the use of the spectrogram. It was Kersta's initial voiceprint article that really sparked the field of speaker recognition research. It was also in the 1960's that mathematical, physiological, and computing advances generated tools that would enable modern speaker recognition systems to be developed.

The first fully autonomous successful speaker recognition system was developed in the early 1970s. The system was a multi-modal, text-dependent speaker authentication system developed and used for access control at Texas Instruments. Advances were made over the next twenty years that led researchers closer to a successful text-independent system. Over the past 25 years the thrust of research has been toward text-independent systems.

The NIST SRE is a test set for text-independent system evaluation. The group of researchers and companies utilizing the NIST SRE has steadily increased. Today research into speaker recognition is a worldwide activity. Commercial ventures into "speaker" biometrics have become more and more common across the globe. With Kersta's initial claim to identifying a voiceprint, speaker recognition has been long anticipated. After all these years of research, speaker recognition appears to be just on the cusp of full-fledge commercial veracity (2% ERR!). In a decade from now perhaps we can claim the speaker recognition problem is a solved problem.

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