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ESTIMATING THE ACCURACY OF AUTOMATICALLY TRANSCRIBED SPEECH WITH PRONUNCIATION IMPAIRMENTS

Abstract

Systems and computer-implemented methods for determining an accuracy of automatically transcribed pathological speech comprise recording speech from a person to obtain an original speech recording; combining a perturbation with the original speech recording to obtain a perturbed speech recording; performing automatic speech recognition, ASR, on the original speech recording to obtain a first transcript; performing automatic speech recognition on the perturbed speech recording to obtain a second transcript; comparing the first transcript with the second transcript to quantify a mismatch between the first transcript and the second transcript.

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Background/Summary

TECHNICAL FIELD

[0001] The present application generally relates to the field of measuring an accuracy of pronunciation of human speech.

BACKGROUND

[0002] Certain disorders, such as autism spectrum disorder (ASD) can result in unclearly articulated human speech.

[0003] An assessment of intelligibility of human speech is usable in the context of automated speech recognition (ASR) and transcription. For example, it can be desirable to detect human speech that is unclearly articulated and exclude it from speech transcripts and the further processing thereof. In a further example, a measure for intelligibility of human speech can be useful when evaluating an ASR service, for example to determine whether malperformance of ASR through the service is due to pathological speech input or due to limitations of the ASR service itself. The terms ASR service, ASR system, and ASR technology are used interchangeably herein unless explicitly mentioned.

[0004] Moreover, an assessment of intelligibility of human speech is usable in the context of diagnosis, clinical study or therapy. For example, it can be desirable to detect human speech that is unclearly articulated as a potential marker of a motor, behavioral or cognitive disorder, and to track its change over time to evaluate disorder progression, treatment response, or to help affected individuals monitor and adapt their speech.

[0005] In the field of ASR, recognition performance is commonly measured in terms of a word error rate (WER). The WER is a standard metric which measures a mismatch between the output of an ASR service in response to a speech recording and a corresponding human transcript of the same speech recording, i.e., a reference transcript, which is a transcript created by a human listener. The WER is computed as the edit distance between the ASR output and the human transcript (i.e., the number of words that need to be inserted, deleted or substituted in order to make the ASR output identical to the manual human transcription), divided by the total number of words in the human transcript. The WER is a rational number value greater than or equal to 0. A WER of 0 specifies a perfect match of the ASR output with the human transcript, whereas a WER of 1 indicates that the number of edits (insertions, deletions or substitutions) that are needed to make the ASR output equal to the human transcript is as large as the number of words in the human transcript. A WER value greater than 1 is possible if, for example, the ASR output contains many more words than the human transcript, i.e., the number of deletions needed is greater than the number of words in the human transcript.

[0006] The WER is an objective measure of the accuracy of a speech transcription. Objective in this context means that the measure is independent of the implementation of a specific ASR service and usable to compare recognition accuracy across different ASR services. The WER is a function of the input and the output of an ASR service. In other words, different ASR services that create the same output from the same input have identical WERs.

[0007] The determination of the WER requires a reference transcript. At least for speech for which such a reference transcription is not available or known upfront, the preparation of a reference transcript by a human is a laborious process and is therefore inconvenient in practice.

[0008] Unclear pronunciation in a speech input can reduce the ability of an ASR service to produce a correct transcript, i.e., to achieve a low WER. Conversely, a high WER can be indicative of unclear or uncommon pronunciation of the speech input, poor audio quality (noise, reverberation), unexpected pronunciation (accents), unexpected words (vocabulary, slang), or unexpected sentences (e.g. the utterance “the sky is boo” would be transcribed as “the sky is blue” by most ASR systems).

[0009] Many ASR systems produce a so-called confidence score for each word in an automatically generated transcript. The confidence score is typically a rational number between 0 and 1. The confidence score specifies a probability with which a given ASR service determined the respective word as a transcription of the speech input. A confidence score of 1 indicates that the ASR is certain about the result of the recognition, whereas a confidence score close to 0 indicates that result of the recognition is very uncertain, such as randomly chosen. Analogous to the confidence score of individual words, an ASR system may determine an overall confidence score for a sequence of words of an entire sentence or transcript. For example, confidence scores for words may be primarily driven by the acoustics of the speech input; the algorithmic piece for this is the Acoustic Model. In contrast, confidence scores for sentences would typically consider the likelihood of the word sequence in a language, as determined by a Language Model. As an example, a language model will make the decision between “recognize speech” and “wreck a nice beach” (similar acoustics but different words) based on the surrounding context. More recently, many ASR systems have moved to so-called End-to-End architectures, where there is no explicit separation between Acoustic and Language Models anymore. In summary, the overall confidence score for a transcript can be different from the mean of the confidence scores of individual words.

[0010] The overall confidence value is a measure for the accuracy of an automatic transcription since the value is determined by the ASR service itself based on the speech input, the internal implementation of the ASR, its internal ASR parameters, and related statistical models. Therefore, the confidence score is a function of the speech input and internals of an ASR system. In other words, different ASR systems that create the same output from the same input can still have different overall confidence scores for their respective recognition process.

[0011] Some conventional techniques for estimating the reliability of automatic transcripts are based on the confidence score. To mitigate the bias for specific ASR implementations and their internal parameters, other conventional techniques combine features from multiple different ASR systems to produce alternative confidence scores and/or transcriptions of one and the same speech input recording to estimate an improved measure of ASR transcription accuracy.

[0012] Since the determination of a WER for a recognition or transcription task is afflicted with the above problem of manually determining a reference transcription, the overall confidence score is frequently used as an estimation or approximation of the true WER. However, such estimation may be inaccurate as will be shown herein. In some cases, depending on the ASR service and its implementation, there is little correlation between the true WER and the overall confidence score.

[0013] It is therefore an objective of the technology described herein to provide an accurate estimator for the WER in automated speech recognition that is robust, i.e., not dependent on a specific ASR implementation, and that does not require manual creation of a reference transcription.

[0014] Furthermore, as explained above, the confidence score is an approximation of a WER and is dependent on the specific implementation of an ASR service.

[0015] It is a further objective of the present technology to provide an assessment of speech intelligibility for a given speech input that is largely independent of the specifics of different ASR technologies and their implementation.

SUMMARY

[0016] A simplified summary of some embodiments of the disclosure are provided in the following to give a basic understanding of these embodiments and their advantages. Further embodiments and technical details are given in the detailed description presented below.

[0017] According to an embodiment, a computer-implemented method for determining an accuracy of automatically transcribed pathological speech comprises: recording speech from a person to obtain an original speech recording; combining a perturbation with the original speech recording to obtain a perturbed speech recording; performing automatic speech recognition, ASR, on the original speech recording to obtain a first transcript; performing automatic speech recognition on the perturbed speech recording to obtain a second transcript; comparing the first transcript with the second transcript to quantify a mismatch between the first transcript and the second transcript. An advantage of this embodiment is that the mismatch has a high correlation to the presence of pronunciation errors in the original speech recording. This correlation reflects the presence of pronunciation errors more accurately than an overall confidence score provided by conventional ASR systems. Unlike such overall confidence score, the mismatch is largely independent of the underlying ASR system that is used.

[0018] In some embodiments, the perturbation is one or more of: additive noise, multiplicative noise, reverberation, decomposing the original speech recording into a parametric representation and re-synthesizing it after varying one or more of the parameters, and speech-like noise obtained by combining fragments of speech from one or more different voices. This aspect has the advantage that the determined mismatch reliably reflects words that are unclearly pronounced, since the specific types of perturbation tend to specifically impact the recognition of conventional ASR systems for words that are unclearly pronounced. In other words, the choice of perturbation is suitable to increase the level of uncertainty of recognition in current ASR systems exactly for those words in the original audio recording that are unclearly pronounced.

[0019] In some embodiments, the signal-to-noise ratio when combining the perturbation with the original speech recording is larger than 0 and lower than 40 dB. This aspect has the advantage that the effect of perturbation is limited in a meaningful degree, so that words that are clearly pronounced can still be reliably recognized by the ASR, and for words with unclear pronunciation, recognition is hampered, such that ASR will more likely err on these unclearly pronounced words. Too much perturbation would deteriorate the recognition rate of clearly pronounced words, too little perturbation would have too little impact on deteriorating the ASR's recognition accuracy of unclearly pronounced words in the original audio recording.

[0020] In some embodiments, the signal-to-noise ratio is determined by: performing ASR on each of one or more test speech recordings for which a word error rate is known to obtain one or more original test transcripts; iteratively performing the steps of combining a perturbation with each of the test speech recording at a test signal-to-noise ratio to obtain one or more perturbed test speech recordings; performing ASR on each of the perturbed test speech recordings to obtain one or more perturbed test transcripts, comparing the original test transcripts with the respective perturbed test transcripts to determine a transcript mismatch measure; varying the test signal-to-noise ratio based on the transcript mismatch measure; until a maximum correlation between the transcript mismatch measure and the known word error rate is achieved, wherein the signal-to-noise ratio is determined based on the current test signal-to-noise ratio. This has the advantage that an ideal signal-to-noise ratio can be determined according to which the perturbation is combined into the original audio speech signal.

[0021] In some embodiments, quantifying a mismatch between the first transcript and the second transcript includes determining a difference as a measure of accuracy of the first transcript.

[0022] In some embodiments, the automatic speech recognition on the original and on the perturbed speech recording is performed using a same ASR technology. In that manner, a mismatch due to different recognition algorithms in different ASRs can be avoided. Such mismatch is undesirable and would be misleading in the above described determination of pronunciation errors.

[0023] In some embodiments, the method further comprises: comparing the measure of transcript accuracy with a measure of transcript accuracy obtained from prior speech recordings of the same person to assess a change in unclear pronunciation of the person and/or to track a level of language development of the person. In that manner, a person can track the development and quality of her own pronunciation over time.

[0024] In this embodiment, optionally, a change in a cognitive status of the person is assessed based on a change in unclear pronunciation. Also, optionally, one or more of a cognitive or behavior disorder of the person and autism spectrum disorder, ASD, are tracked.

[0025] In some embodiments, the method further comprises comparing the measure of transcript accuracy with a measure of transcript accuracy obtained from speech recordings from one or more persons different from the person to determine unclear pronunciation as a pronunciation impairment of the person and/or to track one or more of a level of language development or pronunciation accuracy of the person and a motor or behavioral impairment affecting pronunciation of the person, wherein the one or more persons different from person preferably belong to age-, gender-, and education-matched healthy controls. In that manner, a person compares the quality of her own pronunciation with a control group and tracks the development of her own pronunciation over time.

[0026] In some embodiments, the unclear pronunciation relates to word-finding difficulties, other types of language attrition, or incoherent speech.

[0027] In some embodiments, the speech is pathological due to pronunciation impairments of the person.

[0028] In some embodiments, the pronunciation impairments relate to individual words and/or comprise one or more of hypoarticulation, hyperarticulation, slurred speech, stutter, and mumble.

[0029] The technology disclosed herein can also be embodied in a data processing device comprising a processor adapted to perform the steps of the method for determining an accuracy of automatically transcribed pathological speech according to the methods specified hereinabove.

[0030] The technology disclosed herein can also be embodied in a computer program comprising instructions that, when the program is executed by a computer, cause the computer to carry out the steps of the method for determining an accuracy of automatically transcribed pathological speech according to the methods specified hereinabove.

[0031] The technology disclosed herein can also be embodied in a computer-readable medium comprising instructions that, when executed by a computer, cause the computer to carry out the method for determining an accuracy of automatically transcribed pathological speech according to the methods specified hereinabove.

[0032] The present technology provides one or more the advantages and technical effect described hereinabove.

[0033] The foregoing general description and the following detailed description are exemplary and explanatory only and are not restrictive of the invention as claimed.

Description

BRIEF DESCRIPTION OF THE DRAWINGS

[0034] The foregoing summary as well as the following detailed description of preferred embodiments are better understood when read in conjunction with the appended drawings. For illustrating the invention, the drawings show exemplary details of systems, methods, and experimental data. The information shown in the drawings are exemplary and explanatory only and are not restrictive of the invention as claimed. In the drawings:

[0035] FIG. **1** is a flowchart showing a computer-implemented method for estimating an accuracy of automatically transcribed pathological speech.

[0036] FIG. **2** shows a model of determining ASR prediction accuracy.

[0037] FIG. **3**A-C are plots of statistical data showing word error rates, WER, per recording vs a conventional mean confidence score per recording created by three different ASR services.

[0038] FIG. **4**A-C are plots of statistical data showing WER per recording vs WER between two automatic transcripts generated according to the present disclosure using three different ASR services.

[0039] FIG. **5** is a chart plot comparing the prediction of transcription accuracy based on conventional methods of mean confidence scores with the method according to the present disclosure for three different ASR services.

[0040] FIG. **6** is a schematic block diagram of a data processing device adapted to perform methods for determining an accuracy of automatically transcribed pathological speech according to at least one example embodiment.

DETAILED DESCRIPTION

[0041] The present disclosure relates to methods and systems for determining and measuring the intelligibility of speech, in particular pathological speech, to the ears of a human listener as well as to the “ears” of a speech-to-text system, also referred to as automatic speech recognition, ASR, system herein. The described technology can produce a measure of unclear pronunciation, which can be clinically relevant in itself, i.e., even if there is no intention to do anything else with the transcripts created by an ASR service.

[0042] FIG. **1** shows a flowchart of a method **100** for estimating an accuracy of automatically transcribed pathological speech. The method **100** is not limited to this purpose and can also be used to provide an objective assessment of speech intelligibility. Speech is pathological due to pronunciation impairments of the person **210** who is speaking, wherein pronunciation impairments relate to individual words and/or comprise one or more of hypoarticulation, hyperarticulation, slurred speech, stutter, and mumble.

[0043] FIG. **2** shows a model of determining ASR prediction accuracy. The elements of FIG. **2** will be described in the context of the method **100** described in the following.

[0044] The method **100** comprises the step of recording **110** speech from a person **210** to obtain an original speech recording **220**. Conventional audio technology may be suitable to implement this task.

[0045] The method **100** further comprises the step of combining **120** a perturbation **230** with the original speech recording **220** to obtain a perturbed speech recording **240**.

[0046] The perturbation **230** can be an audio signal independent of the original speech recording **220** and can be pre-recorded or generated on the fly. The perturbation **230** may take the form of additive noise, which is noise that is added to the original speech recording **220**. The noise can take any form of additive noise, for example color noise. FIG. **2** illustrates component **235** for audio signal processing that performs the step of combining **120** the signal of the original audio recording **220** with the signal of the perturbation **230**. Component **235** is indicated in FIG. **2** with a “P” since it causes perturbation to be added to the original audio recording **220**. Note that the perturbation is indicated in the FIG. **2** as a separate signal **230**, which is an input to component **235**. The arrow between the signal **230** and the component **235** is dashed, which indicates that such a separate signal **230** is optional for the step of combining **120** the original speech recording **220** with a perturbation. In some embodiments, the signal **230** may be a signal independent of the original audio signal **220**. In some embodiments, the signal **230** may be derived from the original audio signal **220**. In some embodiments, the perturbation through component **235** may solely be based on the original signal **220** taken as input to the perturbation. Examples of these cases will be given in the following. For all those cases, we refer to combining **120** a perturbation **230** with the original speech recording **220** to obtain a perturbed speech recording **240**.

[0047] While additive noise is a preferred form of noise, the perturbation **230** may also be an audio signal derived from the audio signal of the original speech recording **220**, for example multiplicative noise. The noise can also take the form of a reverberation of the original speech recording **220** or noise obtained by decomposing the original speech recording **220** into a parametric representation and re-synthesizing it after varying one or more of the parameters such as vocoding of the original speech recording **220** or some other speech recording. This can be thought of as decomposing a musical performance into scores for each instrument (the parametric representation), changing the notes, tempo, scale, instruments etc., and recording an orchestra performing those modified scores (the re-synthesized recording).

[0048] The perturbation **230** can also be speech-like noise obtained by combining fragments of speech from one or more different voices. In one example, such speech-like noise can be babble speech or multi-talker babble speech.

[0049] To summarize, the general approach of the combining in step **120** is to distort or perturb the speech recording. Such distortion or perturbation could be achieved through additive noise, which is preferred, but also through multiplicative noise, reverberation, or speech decomposition and re-synthesis methods such as vocoding.

[0050] The idea behind and the reason for introducing the perturbation **230** and combining **120** the same with the original speech recording **220** is that the words in the original speech recording **220** that are impacted the most by the described perturbation **230** are the ones that were not clearly pronounced and hence are the most difficult to be recognized by an ASR system.

[0051] The combining **120** of the perturbation with the original speech recording **220** may be done at certain signal-to-noise ratio (SNR). Preferred SNR values are larger than 0 dB and lower than 40 dB (Decibel). This range is primarily for a perturbation that is additive speech-like noise, for other types of perturbation a specific range could be broader. In the experimental data shown in FIG. **4**A, **4**B, and **4**C, an SNR value of **20** is used. An iterative process of determining a suitable SNR value is described herein at the end of the discussion of the method **100**.

[0052] The method **100** further comprises the step of performing **130** automatic speech recognition, ASR, on the original speech recording **220** to obtain a first transcript **250**. The transcript is a text string including one or more words corresponding to the speech in the original speech recording. The method is independent of the particular ASR technology **280** used for this step, so that any present or future ASR technology may be used to perform step **130**.

[0053] The method **100** further comprises the step of performing **140** automatic speech recognition on the perturbed speech recording **240** to obtain a second transcript **260**. The ASR technology **290** used in this step **140** is preferably identical to the ASR technology **280** used to in step **130**.

[0054] ASR used in steps **130** and **140** may be implemented in a distributed computing environment, such as by cloud computing service. In such a scenario. the steps **130** and **140** may involve transferring the respective speech recording to a cloud computer, performing ASR in the cloud, and receiving the resulting transcription from the cloud.

[0055] The method **100** further comprises the step of comparing **150** the first transcript **250** with the second transcript **260** to quantify a mismatch between the first transcript **250** and the second transcript **260**. In one example, quantifying a mismatch can include determining a difference as a measure of accuracy **270** of the first transcript **250**. Component **265** for quantifying a mismatch between the transcripts is shown in FIG. **2** and may be implemented using ordinary string processing. Comparing **150** the first transcript **250** and second transcript **260** includes quantifying a mismatch between the first transcript **250** and the second transcript **260**. Specifically, in one example, a difference between the two transcripts can be determined as numerical value based on a pairwise comparison of pairs of words. Therein, each word of a pair is taken from each sequence, wherein the difference is a counter of words in the transcription of the original speech recording, i.e., the first transcription that differed from the corresponding word in the transcription of the perturbed speech recording, i.e., the second transcription. The comparison may detect and handle a situation where a word in one transcript is absent in the other transcript and count such situation, for example, as if a pair of differing words was encountered. A measure of difference can be the total number of differences as well as a relative value such as a fraction of words of the entire transcript for which differences are identified during the comparison **150**. Such measure of difference is also referred to as transcript mismatch number or transcript mismatch ratio herein.

[0056] A suitable SNR value for the step of combining **120** can be determined, for example, iteratively and up front, by using multiple recordings, e.g., test recordings, for which the WER obtained in combination with a particular ASR service is known. The SNR value is varied in the iterative optimization process such as to maximize the correlation and/or to minimize the error between our “transcript mismatch” measure, and the actual word error rates of the first transcripts. Essentially, the process is using a set of test recordings, e.g., at least **20**, and varying the SNR until the obtained measure shows the best agreement with the actual ground truth transcription accuracy or intelligibility.

[0057] Thus, an “ideal” SNR is determined, for example, by the steps of performing ASR on each of one or more test speech recordings for which a WER is known to obtain one or more original test transcripts; iteratively performing the steps of combining a perturbation with each of the test speech recording at a test signal-to-noise ratio to obtain one or more perturbed test speech recordings and performing ASR on each of the perturbed test speech recordings to obtain one or more perturbed test transcripts; comparing the original test transcripts with the respective perturbed test transcripts to determine a transcript mismatch measure; varying the test SNR based on the transcript mismatch measure; until a maximum correlation between the transcript mismatch measure and the known WER is achieved, wherein the SNR is determined based on the current test SNR.

[0058] The method **100** optionally includes the further step of comparing **160** the measure of transcript accuracy **270** with a measure of transcript accuracy obtained from prior, e.g., historical, speech recordings.

[0059] The measure of transcript accuracy obtained from prior speech recordings can be based on speech recordings of the same person **210** to assess a change in unclear pronunciation of the person **210** and/or to track on or more of a level of language development of the person **210**. Unclear pronunciation relates to word-finding difficulties, other types of language attrition, or incoherent speech. Tracking changes in pronunciation of a person **210** over time is a key use case for digital biomarkers.

[0060] The method **100** optionally further comprises the step of assessing, based on the change in unclear pronunciation, a change in a cognitive status of the person **210** and/or to track on or more of a cognitive or behavior disorder of the person **210** and autism spectrum disorder, ASD.

[0061] The measure of transcript accuracy obtained from prior speech recordings can be prior speech recordings from one or more persons different from the person **210**, where the one or more persons different from the person **210** preferably belong to age-, gender-, and education-matched healthy controls, i.e. a control group of people with the same gender and same or similar age and education etc. In this example, the comparison enables determining unclear pronunciation as a pronunciation impairment of the person **210** and/or to track one or more of a level of language development or pronunciation accuracy of the person **210** and a motor or behavioral impairment affecting pronunciation of the person **210**. In the use case of comparing with prior speech recordings from other persons, the focus is on pronunciation compared to the general population, e.g., for diagnosis (“pronunciation impairment detected”) or therapy (“pronunciation accuracy is back to normal”). In those use cases, the comparison would be made to scores obtained from age-, gender-and education-matched healthy controls, not to prior recordings of the same person.

[0062] FIGS. **3**A to **3**C illustrate plots of statistical data showing WER per speech recording vs. a conventional mean confidence score per recording created by three different ASR services. The plots in FIGS. **3**A to **3**C will be used to demonstrate shortcomings of conventional WER estimation based on ASR confidence scores.

[0063] Commercial ASR services produce confidence scores for each word in a transcript. FIGS. **3**A, **3**B, and **3**C show experimental data for three different ASR services respectively and demonstrate that the mean confidence scores are not good predictors of errors, specifically the WER, in automatically generated transcripts, when the transcript is compared to a human transcription. In each Figure, a point cloud is shown, wherein each dot of the point cloud represents a transcription experiment. For each experiment, the y-coordinate shows the true WER of the transcript as created by the ASR service to which the Figure corresponds. WER values are non-negative numbers, wherein lower values represent a higher quality transcription. The x-coordinate represents the mean confidence score across all words of a transcription in a recording. Mean confidence scores range between 0.0 and 1.0, wherein higher values respect higher confidence, suggesting a lower WER.

[0064] The plots in FIGS. **3**A, **3**B, and **3**C show the following: First, the correlation is not particularly high, indicating R.sup.2 correlation coefficients between 0.3508 and 0.6109. Second, the mean confidence scores greatly vary across different ASR services. In summary, these experimental results show that the mean confidence score is not a reliable estimation of the true WER rate.

[0065] FIGS. **4**A to **4**C illustrate plots of statistical data showing WER per recording vs. a difference measure between two automatically generated transcripts, namely a first transcript **250** of an original speech recording **220** and a second transcript **260** of a perturbed speech recording **240**, according to the present disclosure, using three different ASR services. The transcript mismatch ratio **270** determined in step **150** provides an estimation of a WER of the transcript as shown with reference to FIG. **4** and discussed in the following. The plots in FIGS. **4**A to **4**C will be used to demonstrate the advantages of WER estimation according to technologies of the present disclosure.

[0066] FIGS. **4**A, **4**B, and **4**C show experimental data obtained from using ASR system A, B, and C respectively. Each dot in the graphs represents one experiment, which means that each dot corresponds to a speech recording for which a reference manual transcription is available and the true WER when transcribed using ASR system A, B, or C respectively is known. The WER may take values greater than or equal to 0. The lower the WER, the more accurate the transcription. The true WER of each speech recording is projected on the y-axis. The x-axis shows the difference measure between a first transcription obtained through the respective ASR on the original speech recording and the second transcript on the corresponding perturbed speech recording using the same respective ASR. The difference measure is obtained using the techniques described hereinabove. The lower the difference measure, the fewer differences exist between the first original, and the second, perturbed, transcripts. The difference measure may take values greater than or equal to 0. The perturbation and the original speech recording were combined with a SNR of 20. The perturbation was based on a multi-talker babble speech.

[0067] The point clouds in each of the graphs corresponding to the respective ASR service are quite linear, which means that there is a relatively strong correlation between the true WER and the difference measure. FIGS. **4**A, **4**B, and **4**C indicate R.sup.2 correlation coefficients between 0.6227 and 0.7390 for different ASR services. In other words, the difference measure, also referred to as transcript mismatch ratio or ASR reliability measure, is an accurate estimator for the WER. Furthermore, the difference measure is a reliable predictor of ASR accuracy, i.e., the difference measure is mostly independent of the specific ASR technology used. In other words, the ASR reliability measure, expresses how well the given speech recording may be handled by multiple different ASR technologies.

[0068] Since the difference measure has a strong correlation with the WER, and since it is not tailored to the particular ASR technology that is used, the measure is reliable indicator of the presence of unclear pronunciation in an original speech recording. In addition, for a particular speech recording, the difference measure can be determined according to the methods presented herein even when the real WER for the original recording on the ASR that is used is not known.

[0069] The technology described herein, which includes adding a perturbation, such as speech-like noise, is dependent on how the ASR deals with this perturbation. Specifically, the effectiveness of determining an accuracy of automatically transcribed pathological speech according to the technologies presented herein relies on the ASR's difficulty of recognizing speech in noise. In other words, a future imaginary and more advanced ASR system may be able to perfectly separate a speaker's voice from that of the additive noise/perturbation and could render the methods of determining an accuracy of automatically transcribed pathological speech presented herein inoperable.

[0070] FIG. **5** shows a chart plot comparing the prediction of transcription accuracy based on conventional methods of mean confidence scores with the method according to the present disclosure for three different ASR services. FIG. **5** effectively summarizes the plots shown in FIG. **3** and FIG. **4** with the following result: The difference measure between two automatically generated transcripts, also referred to as transcript mismatch ratio, provided by the technology disclosed herein is a more precise estimator of the true WER compared to the conventional WER estimators based on confidence scores of different ASR systems. This is apparent since curve **510** is above curve **520** in FIG. **5**. Furthermore, the estimates according to the disclosed technology are more reliable and not tailored to the underlying ASR implementation. This is apparent, since graph **510** is flatter than graph **520**, which shows great variation in the R.sup.2 correlation across different ASR systems.

[0071] FIG. **6** shows a schematic block diagram of a data processing device **610** adapted to perform methods for determining an accuracy of automatically transcribed pathological speech. The device **610** includes a memory **620** and a processor **630**, the processor being in communication with at least on input device **640**, e.g., adapted to obtain a speech recording, and an output device **640**, for example adapted to display the result of a transcription and. Device **610** can be a general purpose processing device, with memory **620** containing instructions that can be executed on the processor **630** and in communication with the memory **620**, in order to perform methods according to the current disclosure. ASR may be performed by the computing device **610** but may also be performed using a cloud service **670** as explained hereinabove, the cloud service **670** being in communication with the computing device **610** through a conventional computer network **660**.

[0072] Aspects of this disclosure can be implemented in digital circuits, computer-readable storage media, as one or more computer programs, or a combination of one or more of the foregoing that implement, or include instructions that implement the methods described herein. The computer-readable storage media can be non-transitory, e.g., as one or more instructions executable by a cloud computing platform and stored on a tangible storage device.

[0073] In this specification the phrase “configured to” is used in different contexts related to computer systems, hardware, or part of a computer program. When a system is said to be configured to perform one or more operations, this means that the system has appropriate software, firmware, and/or hardware installed on the system that, when in operation, causes the system to perform the one or more operations. When some hardware is said to be configured to perform one or more operations, this means that the hardware includes one or more circuits that, when in operation, receive input and generate output according to the input and corresponding to the one or more operations. When a computer program is said to be configured to perform one or more operations, this means that the computer program includes one or more program instructions that, when executed by one or more computers, causes the one or more computers to perform the one or more operations.

[0074] Unless otherwise stated, the foregoing alternative examples are not mutually exclusive, but may be implemented in various combinations to achieve unique advantages. In the foregoing description, the provision of the examples described, as well as clauses phrased as “such as,” “including” and the like, should not be interpreted as limiting embodiments to the specific examples; rather, the examples are intended to illustrate only one of many possible embodiments.

[0075] Further embodiments are described in the following:

[0076] Embodiment 1: A computer-implemented method **100** for determining an accuracy of automatically transcribed pathological speech comprising: recording **110** speech from a person **210** to obtain an original speech recording **220**; combining **120** a perturbation **230** with the original speech recording **220** to obtain a perturbed speech recording **240**; performing **130** automatic speech recognition, ASR, on the original speech recording **220** to obtain a first transcript **250**; performing **140** automatic speech recognition on the perturbed speech recording **240** to obtain a second transcript **260**; comparing **150** the first transcript **250** with the second transcript **260** to quantify a mismatch between the first transcript **250** and the second transcript **260**.

[0077] Embodiment 2: The method **100** according to Embodiment 1, wherein the perturbation **230** is one or more of: additive noise, multiplicative noise, reverberation, decomposing the original speech recording **220** into a parametric representation and re-synthesizing it after varying one or more of the parameters, and speech-like noise **230** obtained by combining fragments of speech from one or more different voices.

[0078] Embodiment 3: The method **100** according to Embodiment 1 or 2, wherein the signal-to-noise ratio when combining **120** the perturbation **230** with the original speech recording **220** is larger than 0 and lower than 40 dB.

[0079] Embodiment 4: The method **100** according to Embodiment 3, wherein the signal-to-noise ratio is determined by: performing **130** ASR on each of one or more test speech recordings for which a word error rate is known to obtain one or more original test transcripts; iteratively performing the steps of combining **120** a perturbation **230** with each of the test speech recording at a test signal-to-noise ratio to obtain one or more perturbed test speech recordings; performing **130** ASR on each of the perturbed test speech recordings to obtain one or more perturbed test transcripts, comparing **150** the original test transcripts **250** with the respective perturbed test transcripts to determine a transcript mismatch measure; varying the test signal-to-noise ratio based on the transcript mismatch measure; until a maximum correlation between the transcript mismatch measure and the known word error rate is achieved, wherein the signal-to-noise ratio is determined based on the current test signal-to-noise ratio.

[0080] Embodiment 5: The method **100** according to one of Embodiments 1 to 4 wherein quantifying a mismatch between the first transcript and the second transcript includes determining a difference as a measure of accuracy **270** of the first transcript **250**.

[0081] Embodiment 6: The method **100** according to one of Embodiments 1 to 5, where the automatic speech recognition on the original and on the perturbed speech recording is performed using a same ASR technology **280**, **290**.

[0082] Embodiment 7: The method **100** according to one of Embodiments 1 to 6, further comprising the step: comparing 160 the measure of transcript accuracy **270** with a measure of transcript accuracy obtained from prior speech recordings of the same person (**210**) to assess a change in unclear pronunciation of the person **210** and/or to track a level of language development of the person **210**.

[0083] Embodiment 8: The method **100** according to Embodiment 7, further comprising the step: assessing, based on the change in unclear pronunciation, a change in a cognitive status of the person **210** and/or to track on or more of a cognitive or behavior disorder of the person **210** and autism spectrum disorder, ASD.

[0084] Embodiment 9: The method **100** according to one of Embodiments 1 to 6, further comprising the step: comparing 160 the measure of transcript accuracy **270** with a measure of transcript accuracy obtained from speech recordings from one or more persons different from the person **210** to determine unclear pronunciation as a pronunciation impairment of the person **210** and/or to track one or more of a level of language development or pronunciation accuracy of the person **210** and a motor or behavioral impairment affecting pronunciation of the person **210**, wherein the one or more persons different from person **210** preferably belong to age-, gender-, and education-matched healthy controls.

[0085] Embodiment 10: The method **100** according to one of Embodiments 7 to 9, wherein the unclear pronunciation relates to word-finding difficulties, other types of language attrition, or incoherent speech.

[0086] Embodiment 11: The method **100** according to one of Embodiments 1 to 10, wherein the speech is pathological due to pronunciation impairments of the person **210**.

[0087] Embodiment 12: The method **100** according to one of Embodiments 1 to 11, wherein pronunciation impairments relate to individual words and/or comprise one or more of hypoarticulation, hyper-articulation, slurred speech, stutter, and mumble.

[0088] Embodiment 13: A data processing device comprising a processor adapted to perform the steps of the method for determining an accuracy of automatically transcribed pathological speech of one of Embodiments 1 to 12.

[0089] Embodiment 14: A computer program comprising instructions that, when the program is executed by a computer, cause the computer to carry out the steps of the method for determining an accuracy of automatically transcribed pathological speech of one of Embodiments 1 to 12.

[0090] Embodiment 15. A computer-readable medium comprising instructions that, when executed by a computer, cause the computer to carry out the method for determining an accuracy of automatically transcribed pathological speech of one of Embodiments 1 to 12.

Claims

1. A computer-implemented method (**100**) for determining an accuracy of automatically transcribed pathological speech, the method comprising: recording speech from a person to obtain an original speech recording; combining a perturbation with the original speech recording to obtain a perturbed speech recording; performing automatic speech recognition (ASR) on the original speech recording to obtain a first transcript; performing ASR on the perturbed speech recording to obtain a second transcript; and comparing the first transcript with the second transcript to quantify a mismatch between the first transcript and the second transcript.

2. The method according to claim 1, wherein the perturbation is one or more of: additive noise, multiplicative noise, reverberation, decomposing the original speech recording into a parametric representation and re-synthesizing it after varying one or more of the parameters, or speech-like noise obtained by combining fragments of speech from one or more different voices.

3. The method according to claim 1, wherein a signal-to-noise ratio when combining the perturbation with the original speech recording is larger than 0 and lower than 40 dB.

4. The method according to claim 3, wherein the signal-to-noise ratio is determined by: performing ASR on each of one or more test speech recordings for which a word error rate is known to obtain one or more original test transcripts; and iteratively performing: combining a perturbation with each of the test speech recording at a test signal-to-noise ratio to obtain one or more perturbed test speech recordings; performing ASR on each of the perturbed test speech recordings to obtain one or more perturbed test transcripts, comparing the original test transcripts with the respective perturbed test transcripts to determine a transcript mismatch measure; and varying the test signal-to-noise ratio based on the transcript mismatch measure; until a maximum correlation between the transcript mismatch measure and the known word error rate is achieved, wherein the signal-to-noise ratio is determined based on the a current test signal-to-noise ratio.

5. The method according to claim 1, wherein quantifying a mismatch between the first transcript and the second transcript includes determining a difference as a measure of accuracy of the first transcript.

6. The method according to claim 1, wherein the automatic speech recognition on the original and on the perturbed speech recording is performed using a same ASR technology.

7. The method according to claim 1, further comprising: comparing a measure of transcript accuracy with a measure of transcript accuracy obtained from prior speech recordings of the same person; to assess a change in unclear pronunciation of the person, and/or to track a level of language development of the person.

8. The method according to claim 7, further comprising: assessing, based on the change in unclear pronunciation and/or language development, a change in a cognitive status of the person, and/or to track one or more of: a cognitive or behavior disorder of the person, or autism spectrum disorder (ASD).

9. The method according to claim 1, further comprising: comparing a measure of transcript accuracy with a measure of transcript accuracy obtained from speech recordings from one or more persons different from the person: to determine unclear pronunciation as a pronunciation impairment of the person, and/or to track one or more of; a level of language development or pronunciation accuracy of the person, or a motor or behavioral impairment affecting pronunciation of the person, wherein the one or more persons different from person belong to age-, gender-, and education-matched healthy controls.

10. The method according to claim 7, wherein the unclear pronunciation relates to word-finding difficulties, other types of language attrition, or incoherent speech.

11. The method according to claim 1, wherein the speech is pathological due to pronunciation impairments of the person.

12. The method according to claim 1, wherein pronunciation impairments relate to individual words and/or comprise one or more of hypoarticulation, hyperarticulation, slurred speech, stutter, or mumble.

13. A data processing device comprising a processor adapted to perform the method for determining an accuracy of automatically transcribed pathological speech of claim 1.

14. A computer program comprising instructions that, when the program is executed by a computer, cause the computer to carry out the method for determining an accuracy of automatically transcribed pathological speech of claim 1.

15. A computer-readable medium comprising instructions that, when executed by a computer, cause the computer to carry out the method for determining an accuracy of automatically transcribed pathological speech of claim 1.