A Case-Based System Architecture based on Situation-Awareness for Speech Therapy

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Keywords: Case-Based Reasoning, Situation Awareness, Speech Therapy, Speech Recognition.

Abstract: Situation Awareness (SA) involves the correct interpretation of situations, allowing a system to respond to the observed environment and providing support for decision making in many systems domains. Speech therapy is an example of domain where situation awareness can provide benefits, since practitioners should monitor the patient in order to perform therapeutic actions. However, there are few proposals in the area that address reasoning about a situation to improve these tasks. Likewise, the case-based reasoning methodology is little approached, since existing proposals rarely use previous knowledge for problem solving. For this reason, this paper proposes a case-based architecture to assist Speech-Language Pathologists (SLPs) in tasks involving screening and diagnosis of speech sound disorders. We present the modules that compose the system's architecture and results obtained from the evaluation using the Google Cloud Speech API. As main contributions, we present the architecture of a system that aims to be situation-aware, encompassing perception, comprehension and projection of actions in the environment. Also, we present and discuss the results, towards a speech therapy system for decision making support.

1 INTRODUCTION

Situation Awareness (SA) has been recognized as an important and yet unsolved issue in many different domains, including physical cyber-security systems, epidemic monitoring and control, intelligent transportation systems, among others (Kokar and Endsley, 2012). The term has been developed simultaneously with the growth of problems interconnected to human factors, since they require skills of perception and decision making. According to Endsley (1995), "practitioners must deal with human performance in tasks that are primarily physical or perceptual, as well as consider human behavior involving highly complex cognitive tasks", thus, it is necessary to conduct actions according to different context information.

In the speech therapy domain, there are few proposals that use knowledge modeling to improve tasks such as diagnosis, therapy planning and therapeutic intervention (Chuchuca-Méndez et al., 2016). Also, clinicians should be supported in achieving a good level of situation awareness about their patient's condition, when decisions need to be taken (Frost and Gabrielli, 2013). In this sense, situation-aware systems represent powerful tools that should aid in the process of diagnosis and clinical support.

Case-based reasoning can also be a favorable choice in speech and health contexts, since this methodology has good learning capabilities, and its ability to solve problems improves as new cases are stored in the history or in a database (Husain and Pheng, 2010). In other words, knowing the solution to a past clinical case (a disease or speech disorder, for example) may be the easiest way to effectively solve a similar case in future.

Given the need for a situation-aware approach focused on speech therapy, we present the architecture of a case-based system that uses prior speech-language knowledge to assist Speech-Language Pathologists (SLPs) in tasks involving screening of speech disorders and decision making. This paper focuses on assessments performed through Google Cloud Speech API and how these evaluations affect the situation perception and classification of speech disorders. We present the analyzes and discuss the results, in order to verify the system usefulness.

Franciscatto, M., Lima, J., Moro, A., Maran, V., Augustin, I., Keske Soares, M. and Cortez da Rocha, C.
A Case-Based System Architecture based on Situation-Awareness for Speech Therapy.
DOI: 10.5220/0006781504610468
In *Proceedings of the 20th International Conference on Enterprise Information Systems (ICEIS 2018)*, pages 461-468
ISBN: 978-989-758-298-1

The present paper is structured as follows. In the next section we present concepts that cover Situation Awareness and Case-Based Reasoning, as well as researches that make use of these concepts. In Section 3 we present our approach of case-based system and assessments performed with Google Cloud Speech API. We discuss the results in Section 4 and conclude with our remarks in Section 5.

2 BACKGROUND

2.1 Case-Based Reasoning

Case-Based Reasoning (CBR) describes a methodology coming from the area of Artificial Intelligence that draws on human reasoning for problem solving. The classic definition is given by Riesbeck and Schank (1989), who point out that "a case-based reasoning solves problems using or adapting solutions to old problems"; that is, a new problem is solved by finding a similar past case, and reusing the information and knowledge of this case in the new problematic situation (Aamodt and Plaza, 1994).

The CBR methodology is commonly described by a cycle of four activities: *retrieving* cases that resemble the description of the problem, *reusing* an existing solution for a similar case, *reviewing* this solution in order to meet the new problem, and *retaining* this solution once it has been confirmed (Watson, 1999).

Case-based reasoning is often used in the exploration of medical or health contexts, where symptoms represent the problem, and diagnosis and treatment are the solution to the problem (Begum et al., 2011). We can mention, for example, the proposal of Husain and Pheng (2010), that addressed the development of a recommendation system for therapy and well-being using hybrid CBR. In the same way, Lee and Kim (2015) proposed a recommendation system that applies CBR for immediate medical services in a cloud computing environment.

2.2 Situation-Awareness

Situation Awareness is a term that expresses "the perception of the elements of the environment within a volume of time and space, the understanding of its meaning and projection of its effects in the near future" (Endsley, 1995). This definition suggests that through situation awareness, applications and systems are able to understand surrounding events and design actions that can offer benefits to human life, from the simple task of providing a personalized service to effective action in risk scenarios.

Situation perception is a critical component for successful actions in complex and dynamic systems, where a poorly planned action may lead to serious results (Oosthuizen and Pretorius, 2015). Thus, situation-aware systems, in addition to dealing with data complexity, must understand contexts and relationships in order to exercise control over situations. Endsley (1995) proposed a model of situation awareness based on three stages: perception, comprehension and projection. In other words, a system is aware of a situation when it gets *perception* about the environment around it, *comprehension* of existing relationships and when it provides *projection* of actions in accordance with the current situation.

2.3 Related Work

Salfinger, Reschitzegger and Schwinger (2013) presented a series of criteria based on components of situation-aware systems that refer to the ability of systems to establish or obtain situation awareness as well as maintain SA over time. According to the authors, in order to obtain SA we must consider input data, domain model, situation assessment and action support provided by the system. Likewise, in order to maintain SA, the following items must be considered: capturing and tracking evolution of situations, projection, incorporation of contextual information, incompleteness and inconsistency of data, SA adaptation, system tuning, knowledge base, incorporation of human intelligence, personalization, explanation and exploration. These criteria were used by Salfinger, Reschitzegger and Schwinger (2013) to analyze approaches in different application domains, including road traffic, maritime surveillance, driver-assistance and airspace monitoring. In the speech therapy domain, we can also use the obtaining and maintaining criteria to analyze and compare approaches, since SA must be explored to face the challenges found in traditional therapy and provide support to SLPs. Thus, a great variety of systems and automatic approaches have been proposed.

Robles-Bykbaev et al. (2016) presented a specialist system for automatic generation of therapeutic guidelines. The specialist system is able to select and suggest the best activities or intervention strategies for a specific patient profile, based on their abilities, limitations and needs. Abad et al. (2013) proposed an automatic speech recognition technology based on a hybrid recognizer, intended for patients with aphasia. Parnandi et al. (2015) presented a system for speech therapy remote administration for children with apraxia of speech, where the SLP can assign the exercises remotely. EchoWear (Dubey

Table 1: Evaluation of related work according to SA criteria proposed by Salfinger, Retschitzegger and Schwinger (2013).

Approach	Gaining SA				Maintaining SA									
					Environment Evolution				System Evolution			Usage Evolution		
	Input Data	Domain Model	Situation Assessment	Action Support	Capturing and Tracking Evolution	Projection	Contextual Information	Incompleteness and Inconsistency	SA Adaptation	System Tuning	Knowledge Base	Incorporating Human Intelligence	Persona-lization	Explanation and Exploration
Robles-Bykbaev et al., 2016	Heterogeneous	yes	Ontology + rules	yes	partially	yes	yes	no	no	no	yes	yes	no	yes
Abad et al., 2013	Heterogeneous	yes	Hybrid recognizer (HMM + MLP)	no	yes	no	yes	partially	yes	partially	yes	yes	no	yes
Parnandi et al., 2015	Homogeneous	yes	HMM decoder. SVM, MLP and MaxEnt classifiers	no	yes	no	no	yes	yes	no	yes	yes	yes	yes
Dubey et al., 2015	Homogeneous	yes	CLIP and SQM computation	no	yes	no	no	partially	yes	no	no	partially	no	yes
Gabani et al., 2011	Heterogeneous	no	Language models, Machine Learning and NLP	no	partially	partially	yes	yes	yes	no	yes	no	no	partially
Schipor, Pentiuc and Schipor, 2010	Heterogeneous	yes	Fuzzy Logic	yes	yes	yes	yes	yes	yes	no	yes	yes	yes	yes
Grzybowska and Klaczynski, 2014	Homogeneous	yes	DTW and kNN algorithms	no	no	no	no	partially	no	no	yes	partially	no	partially
Grossinho et al., 2016	Heterogeneous	no	Naive Bayes, SVM and KDE	no	no	no	no	yes	yes	no	no	partially	yes	yes
Iliya and Neri, 2016	Homogeneous	yes	ANNs and SVM	no	no	no	no	yes	yes	partially	yes	partially	no	yes
Ward et al., 2016	Homogeneous	yes	HNN and HMM decoder	no	partially	no	yes	yes	yes	no	yes	yes	no	partially

et al., 2015) represents another speech therapy system, a smartwatch-based proposal for remotely monitoring speech exercises as prescribed by an SLP. Gabani et al. (2011) explored the use of an automated method to analyze children's narratives in order to identify the presence or absence of language impairment. Schipor, Pentiuc and Schipor (2010) proposed a CBST system (Computer Based Speech Training) based on a therapeutic guide, in order to facilitate the SLP's evaluation and support the therapeutic intervention. Gzrybowska and Klaczynski (2014) presented a software program that uses Automatic Speech Recognition (ASR) technology to identify the speaker's identity. The proposal aims to verify if the articulated sound is the same as the previously recorded models. Grossinho et al. (2016) proposed a phoneme recognition solution for an interactive speech therapy environment. Iliya and Neri (2016) pointed out the need to detect and isolate some parts of speech, so they presented a technique based on neural system to segment speech utterances, where two segmentation models were developed and compared for detecting and identifying sections of disordered speech signals. Finally, Ward et al. (2016) developed a proof-of-concept system based on specialized SLP knowledge to identify and evaluate phonological error patterns in children's speech. An overview of the criteria supported by related work is presented in Table 1.

3 A CASE-BASED SYSTEM FOR SPEECH THERAPY BASED ON SA

3.1 System Architecture

As seen previously, traditional speech therapy presents some obstacles which include, mainly, the lack of specialists in the area and the difficulty of performing adequate patient monitoring. We believe that a situation-aware approach can mitigate these issues, thus the proposed system aims to integrate aspects of the SA Model (Endsley, 1995): Perception, Comprehension and Projection levels.

The first level, *Perception*, is achieved through the collection of speech signals during image naming tasks. In this way, the system is aware of elements in the environment and their current states, evaluating their relevance to decision-making. The *Comprehension* capability should be achieved through assessment tasks performed with Google Cloud Speech API and CMUSphinx (tools for speech recognition). A team composed by speech therapists should provide guidance in this step, collaborating for the understanding of data that may indicate the presence of speech disorders. Also, along the CBR cycle, we aim to increase the system's Comprehension level, basing its actions according to previously diagnosed cases. Lastly, the *Projection* level, should be achieved from the identification and understanding of the patient's situation. Thus, therapists can be supported in the decision-making process, since the case-based system should identify the best solution to deal with a situation and recommend it to the professional.

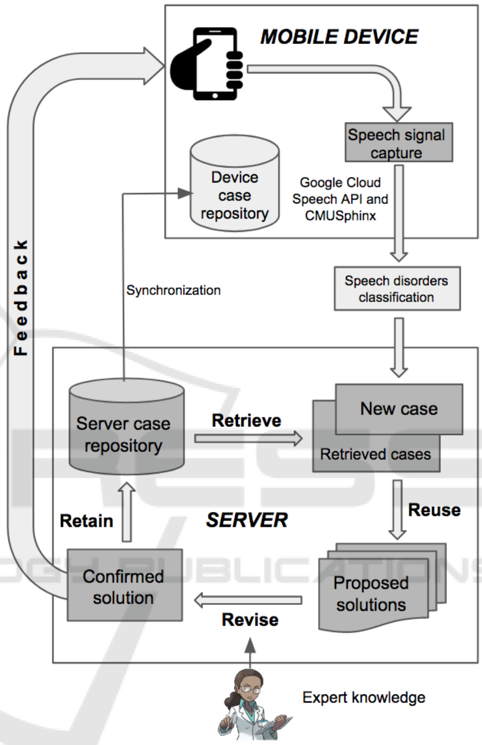

Figure 1: System's architecture.

In order to provide Perception, Comprehension and Projection capabilities, the proposed system architecture consists of two main modules (see Figure 1):

- **Mobile device:** responsible for collecting speech data from the target audience (children aged 3 to 8 years and 11 months) and processing it using two specific tools: Google Cloud Speech and CMUSphinx. The Google Cloud Speech API is used as initial assessment technique, making sure that the collected data is suitable for training acoustic models. The CMUSphinx, in turn, is a public domain software package for implementing automatic speech recognition (ASR) systems (Oliveira et al., 2012). In our proposal, this tool should perform acoustic training, thus, from the input data of a patient, it is possible to classify him/her as a healthy individual or individual with speech disorder.

- **Server:** the server is responsible for taking each patient evaluation analyzed in the previous module as input for Case-Based Reasoning. In other words, the previously classified pronunciation becomes a new case in the server domain, which applies the CBR methodology. Cases that are similar to the new case are retrieved from the repository in order to reuse an existing solution. The solution is reviewed in order to verify if it fits in the new case and, if this solution is confirmed (with speech therapist assistance in the review stage), it is maintained. Thus, the case given as input in the CBR cycle may result in a normal case or a speech disorder case. Considering the last possibility, the system should provide action support to the therapist, indicating what measures can be taken according to the patient's situation. At the end of the whole process, the analyzed case is stored. Synchronization occurs between the server repository and the device repository, so that the knowledge base always remains current with new case data.

3.2 Process of Speech Disorder Assessment

The Google Cloud Speech API performs speech recognition by converting audio to text through machine learning technology. More specifically, the tool applies advanced neural network models and it is capable of performing voice transcriptions in a wide variety of languages. Since the API is a simple way for developers to integrate speech recognition capabilities in their applications (Ballinger et al., 2010), recent researches have used this technology in their methodologies. We can mention, for example, the proposal of Mohamed, Hassanin and Othman (2014), which addressed an educational environment for blind and handicapped people.

In the present paper, we specifically focus our efforts on assessing whether the Google Cloud Speech API (integrated in the first module of the architecture) is adequate for conducting initial speech-language assessments, since the evaluations aim to classify patients as individuals with speech disorders or healthy individuals. The process of speech disorder classification used in the first module of the architecture is demonstrated in Figure 2.

A set of 20 target words in Brazilian Portuguese was selected by a team of speech therapists from the Universidade Federal de Santa Maria (Brazil) in order to assess children's pronunciation skills. This team of

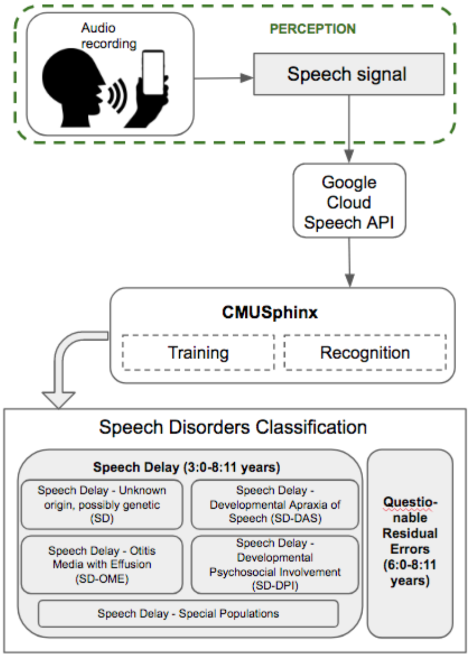

Figure 2: Process of speech disorder classification, used in the architecture.

SLPs performed a series of speech evaluations, which consisted of naming tasks. In these naming tasks, the child was presented to an image (referring to a target word) and should pronounce the word corresponding to this visual stimulus. At the end of each speech evaluation, feedback was given to the SLP through the mobile device, stating whether the child's pronunciation was correct or incorrect, along with the transcript of what was understood by the API (see Figure 3). In total, 31.752 evaluations were performed with 1.362 children aged 3 to 8 years and 11 months.

Figure 3: Screenshots of the mobile application performing speech assessments with Google Cloud Speech API (incorrect and correct pronunciation feedback from the word corresponding to the English word "house").

The speech signals collected from each naming task via mobile device were processed by Google Cloud Speech tool. A file was generated containing the speech data of each child and associated metadata (personal and contextual information of the individual, as well as the transcripts of each audio) for specialist's use. The results obtained from our analyzes are discussed in the next section.

4 DISCUSSION OF RESULTS

From a total of 31.752 evaluations performed, the architecture, using Google Cloud Speech, returned a transcript result to 11.641 of them. For the rest of the evaluations (20.111), the tool was not able to understand the spoken sentence. Table 2 shows the results obtained from the 11.641 cases in which there was a response from the API used. We consider, for each target word:

- **GCS1SLP1:** Number of evaluations in which Google Cloud Speech considered the pronunciation *correct* (1) and the SLP considered it *correct* (1).
- **GCS1SLP0:** Number of evaluations in which Google Cloud Speech considered the pronunciation *correct* (1) and the SLP considered it *incorrect* (0).
- **GCS0SLP1:** Number of evaluations in which Google Cloud Speech considered the pronunciation *incorrect* (0) and the SLP considered it *correct* (1).
- **GCS0SLP0:** Number of evaluations in which Google Cloud Speech considered the pronunciation *incorrect* (0) and the SLP considered it *incorrect* (0).

We considered a Concordance Rate (CR) composed of cases in which the Google Cloud Speech API and the SLP considered the child's pronunciation as *correct* added to the cases in which both considered the pronunciation as *incorrect*. Thus, we have **CR = GCS1SLP1 + GCS0SLP0**. Likewise, we established a Discordance Rate (DR) composed of cases in which the API and the SLP considered different results for the analyzed pronunciation, so that **DR = GCS1SLP0 + GCS0SLP1**.

As shown in Figure 4, from the 11.641 evaluations in which the Speech API returned a transcription result, CR reached 39,41% of the cases, showing concordance between the therapist and the API, while there was a DR in 60,59% of the cases. We can observe that the cases in which the child's pronunciation was considered *incorrect* by the API and *correct* by the therapist (GCS0SLP1) reached the highest percentage among the comparative: 56,90%. We believe that this high score is due to the low sound quality, since there was no adjustment or modification on the speech signal before the processing stage. Also, it can be observed that the Discordance Rate reached a very high value (greater than 50%), demonstrating that the majority of responses from the API do not coincide with the answers given by the SLP responsible for the pronunciation assessments. These results indicate, therefore, that the Google Cloud Speech is not the most indicated tool for speech-language screening tasks, since it did not reached the expected CR rate.

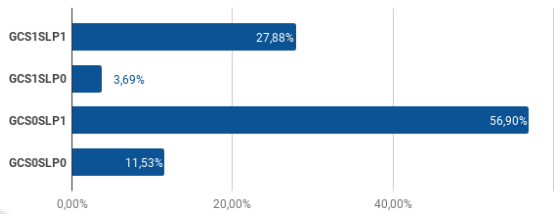

Figure 4: Percentage of concordance and discordance between GCS API and SLP assessments.

However, it is important to note that the SLPs who participated in the evaluation process considered, in addition to the speech data, contextual information as child's age and region to classify the pronunciation. The justification is that words pronounced with an accent can be considered correct in certain regions and incorrect in others. On the other hand, evaluations with Google Cloud Speech API were performed without contextual information integrated to speech data, indicating that context influences the potential of the API and the values of the calculated rates.

Besides that, we did not apply any preprocessing, filtering or adjustment technique in the collected speech signals, in the same way that we did not use any method to optimize the processing performed by the tool. Thus, even with the low value reached by the CR rate (39.41%), we consider this result very promising. In other words, we believe that CR can reach high values if strategies are included to deal specifically with incomplete, noisy or inconsistent data.

5 CONCLUSIONS

In this work, a case-based system was proposed to assist Speech-Language Pathologists in tasks involving screening and diagnosis of speech disorders. Through the literature review, we identified the lack of proposals that cover Case-Based Reasoning for prob-

Table 2: Target words assessments.

Portuguese word	English word	Assessments	GCS1SLP1	GCS1SLP0	GCS0SLP1	GCS0SLP0
Caminhão	Truck	631	310	10	293	18
Cachorro	Dog	586	249	21	265	51
Bebê	Baby	716	271	5	432	8
Casa	House	473	148	2	292	31
Jacaré	Alligator	616	182	42	294	98
Cama	Bed	462	135	3	309	15
Cavalo	Horse	501	146	6	310	39
Coelho	Rabbit	499	136	6	306	51
Jornal	Newspaper	667	174	42	311	140
Cabelo	Hair	797	203	10	547	37
Sofá	Couch	394	97	2	261	34
Bicicleta	Bicycle	543	132	38	221	152
Relógio	Clock	462	110	12	246	94
Gato	Cat	454	107	3	313	31
Batom	Lipstick	530	122	2	394	14
Galinha	Hen	622	142	14	442	24
Cobra	Snake	578	130	30	277	141
Microfone	Microphone	831	180	146	224	281
Folha	Leaf	554	119	17	382	36
Barriga	Belly	725	152	18	507	48
TOTAL		**11641**	**3245**	**429**	**6624**	**1343**

lem solving in the speech therapy domain. Also, we pointed out in Section 2 that SA integration is scarce, so we proposed a system that aims to provide perception, understanding and projection in the environment to ensure dynamism and adaptation in a variety of contexts.

We presented the architecture of the proposed system, describing the modules that constitute it. This paper specifically focused on evaluating the performance of Google Cloud Speech API when executing speech recognition, in order to verify if this tool can be used in speech-language assessments in general.

From speech signals collected from a group of 1.362 children aged 3 to 8 years and 11 months performing image naming tasks, Google Cloud Speech API performed assessments and returned feedback to the specialist stating whether the pronunciation was correct or incorrect. These evaluations were compared with the ones made by the SLP, reaching a Concordance Rate (CR) in 39.41% of the evaluations performed. Although it is a low value, this rate represents a promising result, since no preprocessing techniques were applied to the collected audio, and no contextual information was integrated in the evaluation process performed by the API. We believe that these factors directly interfere with the performance of the tool, which can achieve satisfactory rates with the inclusion of optimization techniques.

From these considerations, our future work includes adding an effective data preprocessing phase, in order to perform data filtering and optimization of sound quality. We are currently investigating the use of Cepstral Mean Normalization (CMN) and Mel-Frequency Cepstral Coefficients (MFCCs) methods for feature extraction operations and noisy data processing. Also, our future work includes testing the performance of other voice recognizers, estimating the SLP's classification through the Google Cloud Speech API, as well as applying the CMUSphinx tool for training and classification of speech disorders. The classified data will be input to the CBR cycle presented in the proposed architecture, which should indicate the appropriate solution based on previous knowledge.

Finally, we conclude that our assessments with Google Cloud Speech presented encouraging results. Through preprocessing strategies, the API can possibly achieve a higher Concordance Rate, so that it can be effectively used as an initial evaluation method before the classification stage foreseen in the architecture. In general, this architecture was designed to integrate capabilities of situation awareness: it should support decision making in speech therapy contexts, recommending the best action to be taken by the therapist according to the identified situation.

ACKNOWLEDGEMENTS

The authors would like to thank CAPES for partial funding of this research and UFSM/FATEC through project number 041250 - 9.07.0025 (100548).

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