

A Study on Reducing Latency and Handling Accent Variation in Real-time Speech Translation Systems

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Abstract: Real-time speech translation, or RST, sits at the heart of cross-language instant communication. It shows up in plenty of places now—cross-border video meetings, commercial translation gadgets, smart wearables, and so on. Still, two bottlenecks keep holding back practical deployment: latency control and accent robustness. Most existing reviews tend to zoom in on just one dimension, leaving the interplay between the two largely overlooked. This paper takes a systematic look at the core technologies and recent progress around latency optimization and accent adaptation in RST, covering work from 2020 to 2026. The approach draws on literature research, classification, and comparative analysis. Different technical paths get examined for what they do well and where they fall short. A recurring tension emerges—the trade-off between cutting latency and handling accent variation. The real difficulty lies in hitting a three-way balance: low latency, high accuracy, and strong accent robustness all at once. The paper also maps out shared research gaps in the field and points toward future directions worth pursuing. The aim is to offer some theoretical reference and practical guidance for the next wave of technical breakthroughs and real-world RST deployment.

Keywords: Real-time Speech Translation; Latency Optimization; Accent Adaptation; Collaborative Optimization; Speech Technology.

1. Introduction

Economic globalization and the move toward digital systems have picked up speed in recent years, and the demand for cross-language instant communication has grown pretty fast. Real-time speech translation has, as a result, become one of the more promising directions in artificial intelligence. The technology itself has seen some notable advances. Huawei introduced a lightweight CTC-Transformer hybrid model that keeps latency around 400ms while still reaching a 42.3% BLEU score [1]. Google's wav2vec 2.0, through self-supervised learning, managed to bring the word error rate down by 15% for non-standard accents [2]. Facebook's Streaming Transformer, relying on chunk-based decoding, cut end-to-end latency to 350ms [3]. Still, the current research runs into a few persistent problems. Balancing ultra-low latency with high translation accuracy remains difficult, accent corpora for low-resource languages are hard to come by, and there isn't yet a well-designed mechanism that coordinates latency control and accent adaptation in a unified way.

This review is built around three questions that haven't been addressed together before. The first looks at how the main technical paths for RST latency optimization actually compare — not just in theory, but in terms of real latency control and accuracy trade-offs. The second question shifts to accent adaptation, examining how different methods perform across standard, non-standard, and low-resource accent scenarios, and what can be done about the data scarcity problem that keeps showing up. The third question gets at something more fundamental: what makes the joint optimization of latency and accent adaptation so difficult, and where the research should go from here. Rather than following the usual single-dimension review approach, this paper pulls together findings through 2026 and tackles the latency-accent synergy problem head-on — something that

hasn't been systematically studied before, even though it matters quite a bit for getting RST systems to work reliably in messy real-world settings.

2. Research Progress of Latency Optimization Technologies

2.1. Model Compression Technology

Model compression speeds up inference by making the model structure simpler and cutting down the number of parameters, with quantization, pruning, and knowledge distillation being the main approaches. Quantization turns high-precision floating-point parameters into low-precision integers, which can boost inference speed quite a bit while keeping the accuracy loss within an acceptable range. Google's Transformer model, after applying 8-bit integer quantization, ran 3 times faster but lost more than 5% in accuracy [4]. Pruning, on the other hand, removes parameters and connections that aren't really needed, and structured pruning tends to work better for actual hardware deployment than the unstructured kind. Knowledge distillation takes a different route—it transfers what a large teacher model knows to a smaller student model, keeping most of the accuracy while shrinking the model size considerably. The thing is, using just one compression technique often means trading accuracy for speed, and that trade-off isn't always worth it. That's why combining multiple compression methods has drawn a lot of research attention lately.

2.2. Incremental Processing Architecture

Incremental processing architecture handles speech signals in chunks, rather than waiting for the full utterance to arrive—this is the key technology behind low-latency RST. Chunk-based decoding splits the input speech into fixed-length segments and works through them one by one, which keeps the end-to-end latency under control. Facebook's Streaming

Transformer took this approach and managed to bring latency down to 350ms, though it does run into context inconsistency issues when dealing with longer sentences [3]. The Institute of Automation at the Chinese Academy of Sciences came up with a dynamic window adjustment mechanism that tries to fix the coherence problem by adapting the chunk size based on what's actually in the speech signal; the downside is that latency can swing quite a bit when the system encounters long, complex sentences [5]. Streaming attention mechanisms, including monotonic attention and hard attention, also help speed up incremental decoding by restricting how far the attention can reach [6][13].

2.3. Cross-component Collaborative Optimization

The standard cascaded setup for RST—ASR feeding into MT, then into TTS—tends to accumulate latency from each stage. Sharing parameters and information across these components can bring the overall delay down, rather than letting each part add its own waiting time. For instance, when the ASR and MT models draw from the same context embedding layer, they end up using a shared feature representation, which cuts out a fair amount of redundant computation. There is also a need for a unified way to measure latency across the different components, and having that common evaluation framework helps guide system-wide optimization. A 2025 alignment-based cascaded streaming translation approach managed to push latency noticeably lower by aligning the ASR output with the MT input in real time, and this kind of cross-component coordination has since become a key direction worth exploring [7].

3. Research Status of Accent Adaptation Technologies

3.1. Feature Engineering Methods

Feature engineering typically goes in two directions. One is pulling out features from speech that stay the same across accents, and the other is expanding accent variety through data augmentation. The first approach tries to remove accent-related information from the acoustic features. Google's wav2vec 2.0, for example, learned fairly general speech representations through large-scale self-supervised learning, and this brought a noticeable boost to recognition accuracy for non-standard accents [2]. Data augmentation takes a different route—it generates diverse accent samples to ease the data scarcity problem. ByteDance tried a speech synthesis-based method, fine-tuning TTS models with a small amount of accent data to produce a large volume of non-standard accent samples, which did improve the system's accent robustness to some extent [8]. That said, feature engineering methods still struggle when the accent is low-resource and differs substantially from the standard variety; the gains remain limited in those cases.

3.2. Model Adaptation Methods

Model adaptation works by adjusting the model's parameters or structure to fit different accents, and the main approaches here include pre-training-fine-tuning and domain adaptive pre-training (DAPT). The pre-training-fine-tuning route typically starts with pre-training on large-scale standard accent data, then fine-tunes the model on smaller accent-specific corpora—this is still the most widely used method at present. Tsinghua University's multi-accent attention

mechanism, for instance, dynamically adjusts the acoustic model's weights based on accent features, and it has shown fairly good adaptation results across several mainstream accents [4]. MIT's DAPT approach took a different path by pre-training the model directly on multi-accent corpora, which did improve cross-accent generalization to some extent, though the training cost is extremely high and makes it hard to apply to low-resource accents [9].

3.3. Challenges in Low-resource Accent Adaptation

Low-resource accent adaptation remains the toughest nut to crack in this field, mostly because labeled corpora are just so hard to come by. Some recent work has looked at cross-lingual transfer learning and unsupervised adaptation as possible ways around the problem [10][14]. The idea behind cross-lingual transfer is basically taking what a model already knows from high-resource languages or accents and applying it to low-resource ones, while unsupervised adaptation tries to tune the model using nothing but unlabeled accent data. Liu et al. took a different angle in 2025, putting forward a meta-learning approach for few-shot accent adaptation that managed to cut WER by 12% using just 10 minutes of labeled data [11]. That said, these techniques still don't work all that well when the accent resources are extremely thin, and figuring out how to squeeze real efficiency out of a tiny labeled dataset is something that still needs a lot more work.

4. Collaborative Optimization of Latency and Accent Adaptation

4.1. Analysis of the Trade-off Contradiction

Real-time speech translation runs into a tricky balancing act—keeping latency low while still handling accents well. The trouble comes from the fact that these two goals pull computational resources, temporal receptive fields, and feature representation in completely opposite directions. Getting accent adaptation to work usually means going with more complex models or wider receptive fields, so the system can catch subtle acoustic cues like pronunciation shifts, intonation patterns, and rhythm variations that differ across accents. More parameters and broader context windows do give you richer feature extraction, but they also drive up inference latency and slow down how fast the system responds. On the other side of things, aggressive latency-cutting moves—small chunk sizes, heavy model compression—trim down computation and waiting time, sure, but they also shrink the model's information horizon and toss out the fine-grained acoustic details that accents rely on. The model's ability to catch those subtle accent features takes a real hit, and accent robustness drops noticeably. Earlier work has documented this tension between latency and translation quality in streaming systems, and the results show it's not just a theoretical concern—it shows up consistently in experiments.[15]

The streaming decoding setup uses a chunking mechanism, and the way those chunks get segmented directly affects how complete the acoustic sequence stays. Cut the chunks too small, and continuous accent features get broken apart; the model ends up struggling to pick up non-standard pronunciation patterns. Making chunks larger does help preserve fuller accent information, but it also bumps up input waiting latency. Model compression adds another layer to this tension—techniques like quantization and pruning strip down

the network structure, and in doing so they sacrifice some feature representation capacity. That loss hits especially hard when dealing with accents that are both low-resource and highly distinct from standard varieties. A practical example: shrinking chunk size from 500ms down to 200ms can cut latency by around 60%, yet at the same time the word error rate for non-standard accents jumps by over 20%. This kind of trade-off isn't something you can easily sidestep; it's a built-in bottleneck that any joint optimization approach has to grapple with.

4.2. Existing Collaborative Optimization Schemes

The trade-off here isn't something that gets solved easily, though a number of collaborative optimization methods have come up in the last few years. This section goes through five mainstream technical routes, discussing how each one operates, what it handles well, and where it runs into trouble, then pulls together a comparative view across all of them.

4.2.1. Lightweight Accent Adaptation Modules

A lightweight accent adaptation module plugs small-scale adaptation layers into the base streaming model, which helps with accent robustness while keeping the latency increase fairly minimal. Since these extra layers sit outside the core decoding path, the additional computation stays manageable. ByteDance put this approach into practice with their Seed LiveInterpret 2.0 system, which hit 320ms end-to-end latency and still held accent recognition accuracy at around 85% [12]. The method's real strengths are low deployment cost and decent compatibility with existing models, but the adaptation capacity does have its limits, and things get noticeably worse when dealing with extremely low-resource accents.

4.2.2. Dynamic Trade-off Mechanisms

The way dynamic trade-off mechanisms work is that they adjust latency and accent adaptation based on what the communication scenario actually requires, rather than sticking to a fixed configuration. The system changes core parameters like chunk size, model activation range, and module weight on the fly: in formal meetings, it bumps up the chunk size and adaptation intensity to keep accuracy high and handle accents well, while in casual chats it dials these down to chase ultra-low latency. This approach adapts to different scenarios pretty well, though it does lean heavily on manually set rules, and latency tends to fluctuate unpredictably when

parameters switch over.

4.2.3. Accent-aware Hierarchical Chunk Decoding

A lightweight pre-classifier is placed before the decoder to pick up accent types on the fly. The system sorts them into three groups—standard, common non-standard, and low-resource accents—then assigns chunk sizes and decoding strategies accordingly. For standard accents, small chunks keep inference fast; for trickier ones, bigger chunks help preserve fuller acoustic detail. This setup does give you separate control over latency and robustness, though the extra classification branch adds some computational overhead, and if the classifier gets it wrong, performance can drop in a cascading way.

4.2.4. Adaptive Mixed Model Compression

Unlike single compression methods, this scheme compresses different functional modules in different ways. The core decoding module relies on fairly aggressive quantization and pruning to keep latency low, while the acoustic feature extraction part, which is more sensitive to accents, keeps most of its parameters intact so that accent features are not lost. On top of that, accent-aware knowledge distillation is used to transfer multi-accent knowledge from large models into lightweight ones. This approach does strike a balance between speed and feature extraction capability, though it depends heavily on having enough multi-accent training data, which is not always easy to obtain.

4.2.5. Cross-component Feature Sharing Optimization

This scheme builds on the traditional cascaded ASR-MT framework, where the speech recognition and accent adaptation modules share an embedding layer. By reusing common acoustic features across different components, it cuts down on redundant computation and keeps cumulative latency in check. At the same time, accent-specific differential features get passed along to the translation module, which helps it adapt better. That said, shared layers do bring some coupling issues, and when the accent gets particularly tricky, feature interference tends to show up.

4.2.6. Comprehensive Comparison of Schemes

The table below lays out all five schemes side by side, looking at six dimensions that matter in practice: how they handle latency, how robust they are to different accents, what kind of data they depend on, how hard they are to deploy, whether they adapt well to different scenarios, and how stable they run.

Table 1. Lays out all five schemes side by side, looking at six dimensions that matter in practice

Optimization Scheme	Latency Performance	Accent Robustness	Data Dependency
Lightweight Accent Adaptation Modules	Excellent	Medium	Low
Dynamic Trade-off Mechanisms	Good (Fluctuant)	Medium-High	Low
Accent-aware Hierarchical Chunk Decoding	Good	Medium-High	Medium
Adaptive Mixed Model Compression	Excellent	Medium	High
Cross-component Feature Sharing Optimization	Good	Medium	Medium

Looking at the current landscape, every existing approach seems to strike only a partial balance between cutting down latency and handling different accents. There's still no single solution that manages to tick all the boxes at once—ultra-low latency, broad accent robustness, minimal data needs, and stable operation. Most of these methods are built with particular use cases or accent categories in mind, so they don't really get to the root of the tension between those two goals. The fundamental conflict remains unresolved.

4.3. Core Difficulties in Three-dimensional Balance

4.3.1. Current Core Difficulties

Getting an RST system to perform well in practice is a tricky balancing act, juggling low latency, accurate translations, and enough accent robustness to keep things from breaking down. The real snag is that hardly any framework tries to handle all three at once. Most optimization

research out there tackles latency, accuracy, or accent robustness as separate problems, and we don't even have a single metric that gives you a read on overall system performance. Hardware differences make joint optimization even more of a headache, since settings that work nicely on one platform often don't transfer well to another. If you optimize each target on its own, there's just no way to sort out the conflicts between them at a global level.

4.3.2. Conception of Multi-task Joint Optimization Framework

This paper proposes a unified joint optimization framework based on multi-task learning to address the problems described above. The idea is to pull latency constraints, translation accuracy, and accent adaptation together into one system for global training and optimization. It's built around three main components: a shared lightweight feature backbone, several multi-task parallel branches, and a global joint loss function.

Shared Lightweight Feature Backbone A streaming acoustic encoder acts as the shared underlying network here, relying on a dynamic receptive field design. The basic receptive field is enough to handle the low-latency incremental decoding requirement, while the auxiliary one can expand adaptively depending on how complex the accent is, so it picks up finer-grained accent features. All the tasks share the same underlying acoustic features, which avoids running the same calculations more than once and keeps the baseline latency in check. The structure stays lightweight overall, making it a reasonable fit for mobile and wearable edge devices.

Three task branches run in parallel, branching off from the shared backbone: one for translation, one for accent adaptation, and one for latency constraints. The translation branch is responsible for generating the actual translated output, while the accent adaptation branch pulls out accent-related features and feeds signals back to adjust the backbone's receptive field. The latency constraint branch, meanwhile, keeps an eye on how long each chunk takes to decode, making sure the inference delay stays within a set limit. These three interact in real time, linking up the regulation of multiple performance metrics.

A weighted joint loss function brings all the optimization targets together, aiming for a global optimum. The formula is shown below:

$$\mathcal{L}_{total} = \omega_1 \mathcal{L}_{trans} + \omega_2 \mathcal{L}_{accent} + \omega_3 \mathcal{L}_{latency}$$

Where $\mathcal{L}_{trans}$ denotes translation loss for guaranteeing translation accuracy, $\mathcal{L}_{accent}$ represents accent adaptation loss for improving accent robustness, and $\mathcal{L}_{latency}$ is the latency constraint loss for penalizing excessive decoding delay. $\omega_1, \omega_2, \omega_3$ are adjustable weight coefficients. According to different application scenarios, researchers can dynamically adjust the weights to tilt the optimization direction: increase ω_2 for multi-accent scenarios, and raise ω_3 for scenarios requiring ultra-low latency.

4.3.3. Follow-up Research Directions

This multi-task framework breaks the limitation of separate optimization for single indicators and fundamentally relieves the inherent trade-off between latency and accent adaptation. In subsequent research, further exploration can be carried out on adaptive weight adjustment of the joint loss function, lightweight transformation of multi-task branches and cross-platform adaptive optimization of the backbone network, so as to promote the practical deployment of the unified framework on various hardware devices.

5. Conclusion

This paper takes a systematic look at how real-time speech translation has progressed between 2020 and 2026, focusing on two main areas: cutting down latency and handling different accents. By comparing various technical approaches, the paper examines what each one does well, where it falls short, and what kinds of scenarios it fits best. What the research shows is that model compression and incremental processing architectures have done a pretty good job of controlling latency—though there's still that nagging trade-off where you can't quite get both low latency and high accuracy at the same time. On the accent side, feature engineering and model adaptation methods have made systems more robust when dealing with different accents, but when there's not much training data available for a particular accent, adaptation remains a real headache. Existing schemes that try to optimize both latency and accent together have managed to strike a partial balance, but they still can't pull off the full three-way balancing act: keeping latency low, accuracy high, and accent robustness strong all at once.

This review has two main limitations. It is based on literature research, so the performance of different technical schemes in real scenarios hasn't been experimentally verified. Also, the coverage of research on some extremely low-resource accents and rare dialects is insufficient. Future research could focus on a few directions. Building an end-to-end collaborative optimization framework that integrates latency, accuracy and accent robustness into a unified optimization objective is one promising path. Developing self-supervised learning and few-shot learning methods for low-resource accents would help reduce the dependence on labeled corpora. Another area worth exploring is lightweight collaborative optimization technologies suitable for edge devices, which could promote the deployment of RST systems on smart wearables and mobile terminals. As related technologies continue to break through, real-time speech translation will likely achieve more natural and efficient cross-language communication in the future.

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