rt-ai Edge Smart Gym Concept

Introduction

Recent advances in machine learning and artificial intelligence are enabling disruptive changes to existing business models. This document shows how rt-ai Edge can transform traditional exercise gyms into AR, MR and AI enhanced spaces that greatly enhance the gym user's experience. Retrofitting this technology into existing gyms would be very easy, meaning that there is already a large potential market for this technology as a packaged solution. The rt-ai Edge smart gym concept provides a demonstration of how rt-ai Edge's powerful design tools and high performance real-time processing building blocks can even be used by non-programmers to create state of the art experiences.

The fundamental object in rt-ai Edge is the Stream Processing Element (SPE). This takes input data in a standard format, processes it in some way and then outputs standard format messages containing the results of the processing. An example would be object recognition and segmentation for a video feed. The use of standardized format messages for each class of data means that these SPEs can be easily joined together form more complex Composable Processing Pipelines (CPPs) which are essentially super-SPEs. These CPPs can themselves be joined together in arbitrary ways to form more complex Stream Processing Networks (SPNs). The design of CPPs and SPNs is performed using rt-ai Designer, a GUI-based tool that makes it very easy for non-programmers to construct complex real-time systems.

Using Technology to Enhance Physical Fitness

Integrating new technologies with physical fitness has been in progress for a while, examples being Peloton in the home gym space and Orangetheory in the commercial gym space. The concept described here combines and extends these concepts to bridge the gap between state of the art commercial gyms and home gyms.

The rt-ai Edge Smart Gym Approach

The rt-ai Edge smart gym combines a number of technology pieces in order to create a new experience:

- The latest smart phones and tablets (such as iPhone XR and iPad Pro) have specialized onboard hardware that can perform inference in real-time on video streams and other data streams. A key advantage of performing onboard inference is that video never leaves the device, addressing users' concerns about what is being done with their video.

- Future lightweight MR headsets with minimal onboard processing power could leverage the edge computing system by offloading all compute-intensive processing to the edge and just acting as a display, camera and sensor interface. In fact, this offload model may be the future of MR headsets in most applications. Gym users could choose to use a mobile device for AR or an MR headset to get the full MR experience.

- Wearable heart rate monitors to assess the user's performance and connected via Bluetooth to the mobile device.

- The dedicated rt-ai smart gym app integrates data from the mobile device's camera and the heart rate monitor and uses inference to generate metadata that can then be sent via WiFi to the gym's systems.

- The gym's AI-enhanced edge computing systems (using rt-ai Edge) can integrate the data from the mobile devices, provide more processing power than available directly on the devices themselves, drive displays with real-time data in the space and connect to back-end cloud services for data persistence and access via offline apps and a website.

- Cloud-based systems for long term persistence of user data and to provide off-line access of a user's performance that the user can review anywhere.

- Technologies such as ARKit and MR headsets means that the gym spatial environment can be augmented with active virtual objects, driven by data being collected in the gym.

The idea is that the user either wears a lightweight MR headset or else the users' mobile device is placed by the user in a holder at each workout station so that the screen and front camera is facing the user. The rt-ai smart gym app uses the screen to provide feedback to the user while the camera is used to derive important metadata. In the case of an MR headset, independent cameras would be required at each workstation as the camera needs to be facing the user to infer activities

The metadata produced within the mobile device would include:

- Location within the gym. This will help to determine the activity being performed.

- Exactly what exercise is being performed. If the user is working with an exercise bike or rowing machine for example, then it is pretty obvious what is happening. Ideally, the machine would communicate with the app to pass along information such as speed, incline, resistance etc. However, at a weight station or other more flexible situation, it is less clear. Here, a trained AI model is used by the mobile device to identify the specific activity from the video stream produced by the mobile device's camera.

- Rep count, weight data etc. Using the metadata, the app can determine how many times an action has been performed and (by mapping the image of weights to known weight data via a trained model specifically for that purpose) with what weights etc. This information is provided to the user using the mobile device's display.
- Form and technique. Using specific models chosen on the basis of the recognized activity, the app performs an analysis of the user's form and technique and can provide feedback via the screen if there are problems.

This metadata drives a display on the mobile device but is also sent to the edge processing system. The edge processing system drives displays within the gym so that everyone can easily see what's happening. In addition, it can provide more complex analysis of user metadata before passing the data up to external cloud storage.

Finally, the gym's edge computing systems use data collected in real-time to create and update virtual objects in the gym space. The user can see these objects by using ARKit on an iPad for example or using MR headsets. This information could be personalized: for example, the AR/MR overlay could show the user the next machine to use in a workout.

Customized Training Videos

A specific example of the AI-enhanced capabilities of the rt-ai Edge smart gym is the creation of customized training videos for each exercise. Using vid2vid (https://github.com/NVIDIA/vid2vid) for example, it would be possible to modify a video of an expert trainer performing an exercise so that the user seems to be performing the exercise correctly. When the user is performing the exercise in real-life, the customized training video and real video (from the mobile device's front camera) would be displayed side by side to give the user instant feedback.

The vid2vid video would be created in the edge computing network, leveraging its inference capabilities and then delivered to the mobile app for display.

Commercial Gyms and Home Gyms

An important aspect of this design is that exercise doesn't have to performed at a commercial gym. A user could have a similar setup at home (where a mobile device is placed with the screen and camera pointing at the user). Due to the use of different equipment, some functions might not work in the same way (such as recognizing weights automatically from their appearance in the video) but there are workarounds for this (manual entry if necessary).

When the app is used in a home gym, metadata is passed via the cloud service back to the gym so that it can be fully integrated, just as though the exercise was performed at the commercial gym and still leveraging the gym's edge computing system as necessary.

rt-ai Edge System Design for the Smart Gym

The rt-ai Edge smart gym system consists of two major components: an app (or apps) for mobile per-user devices and the edge computing system that supports the user apps. The app could be a standard app that is simply branded with the gym's information. The idea is that the app itself is very simple - its specific operation is controlled by the edge computing system.

The edge computing system would be composed of a number of Composable Processing Pipelines, working together to form the complete solution. Some of these CPPs would be statically instantiated as they are required full time - the CPPs that drive the big screens in the gym would be an example of this. Other CPPs would be demand-driven. For example, a set of CPPs would be created whenever a new user enters the gym and torn down when that user leaves.

Examples of CPP functionality includes:

- A per-user CPP that received data from the user's app during exercise and drives processed data back to the user's app for display to the user.
- A per-user CPP that drives the AR/MR display with information such as the next machine in the workout.
- A static CPP that collects data from the per-user CPPs and saves this to local storage and/or cloud storage for offline processing and access.
- A static CPP that drives the shared displays in the gym space using data from the per-user CPPs.

Additionally, there would need to be offline tools to perform functions such as user management for example.

An important point is that the real-time network is dynamic - it is very easy to add and remove CPPs and underlying SPEs as required. Systems would be designed using a combination of standard rt-ai Edge SPEs and CPPs along with vertical-specific SPEs and CPPs. For example, a new CPP could become available for the rt-ai smart gym system that added some sort of useful functionality. Any specific gym could use the rt-ai Edge design tools to rapidly update their real-time design with the new functionality.

Conclusions

The rt-ai smart gym concept illustrates some of the key advantages of rt-ai Edge: the ability to build real-time, inference enhanced flexible edge computing systems that solve real problems. Instead of highly complex, monolithic code, rt-ai Edge joins together simple, easy to understand and test elements (SPEs) to form complex SPNs in a very customizable way.