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MODEL AND STRUCTURE OF MULTIAGENT SYSTEM FOR COLLECTION AND PROCESSING SOUND INFORMATION

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Abstract. A symbolic model of a multi-agent system (MAS) for collecting and processing sound information (CPSI) from the environment was proposed. The model includes agents of input and encoding of local sound information, database agents, knowledge base agents, agents of calculation of integral estimates of the sound situation, decision-making agent. On the basis of this model the structure of the MAC for CPSI consisting of preprocessors for audio input and encoding, wireless communication channels, server and operator console was developed

Keywords: sound preprocessor, databases and knowledge, server, multi-agent system.

Introduction

Collecting and processing the various types of sounds and their spatio-temporal effects becomes crucial. Using a model that embeds the representation of sounds properties on sources, and the rules that govern their propagation across the various surrounding mediums would help in both, tracking the historical variations and predicting the future changes of sounds properties along the spatio-temporal dimensions. In fact, such a model can represent levels of noise in a large urban space and help in studying noise pollution at various layers: inside a given building, in a specific public park or around the whole city. It will also help in predicting how spatiotemporal changes may affect the levels of noise pollution at any of these layers, for instance when a new building complex or a compound community take place in the city.

In fact, the amplitude and effect of sound waves vary considerably across the continuous spatio-temporal dimensions. For instance, the noise produced by a taking-off airplane is perceived by its neighborhood with varying amplitudes over time: it starts loud, and then decreases gradually while it is flying away. On the other hand, data modeling and especially spatio-temporal data is an important phase that gives the users a clear way to understand a case of study and to make a decision [1–3].

Existing approaches to sound processing

The most important classification methods for information processing use Hidden Markov Models (HMM), Gaussian Mixture Models (GMM) and Support Vector Machines (SVM), which will be discussed in below, although there are other useful methods that are summarized as follows [4]:

– *k*-Nearest Neighbours (*k*-NN): a simple algorithm that, given a testing pattern, uses the majority vote of the *k*-nearest training patterns to assign a class label. It is often described as a lazy algorithm, as all computation is deferred to testing, and hence can have a slow performance for a large number of training samples. For the case of the 1-NN, the method has a 100 % recall performance, which is unique.

– Dynamic Time Warping (DTW): the algorithm can find the similarity between two sequences, which may vary in time or speed. It works well with the *bag-of-frames* approach, as it can decode the same word spoken at different speeds. However, it has largely been superseded by HMM for Automatic Speech Recognition (ASR).

– Artificial Neural Networks (ANN): the method, also referred to as a Multi-Layer Perceptron (MLP), is a computational model inspired by neurons in the brain. Given a sufficient number of hidden neurons, it is known as universal approximator, but is often criticized for being a black-box, as the function of each neuron in the network is hard to interpret. It also suffers from difficulty in training, as the most common method of back propagation is likely to get stuck in local minima.

There are many features that can be used to describe audio signals. The feature vector for the experiments consisted of features summarized in [5, 6].

Three different classification methods were investigated: *k*-Nearest Neighbours (*k*-NN) [7], Gaussian Mixture Models (GMM) [8], and Support Vector Machine (SVM) [9]. For *k*-NN, we used the Euclidean distance as the distance measure and the 1-nearest neighbor queries to obtain the results. As for GMM, we set the number of mixtures for both training and testing to 5. For the SVM classifiers, we used a 2-degree polynomial as its kernel with regularization parameter $C = 10$ and the epsilon $\varepsilon = 1 \cdot e^{-7}$, which controls the width of the *e*-insensitive zone, which used to fit the training data, affecting the number of support vectors used.

Multiagent approach and offering model

Multi-agent systems (MASs) have been usually accepted and imbedded in deferent domains applications because of the benefits and advantages which they can offer. Some of them that offered by using Multi-agent systems (MASs) in large systems are [10]:

1. An enhance in the effectiveness and process speed due to parallel computation and asynchronous operation.
2. In case of system degradation (when one or more of the agents fail), common reliability and robustness of the system is acceptable.
3. Scalability and flexibility – agents can be added as required.
4. Reduced cost – individual agents cost much less than a centralized architecture.
5. Reusability – agents have a modular structure and they can be easily replaced in other systems or be upgraded more easily than a monolithic system.

Let's consider the authors' approach to the symbolic description of a multi-agent model for collecting and processing sound information (CPSI) from the environment, based on the concept of object algebra [11]. Let's present this model as a set of agents:

$$MAS_{CPSI} = \left(A_{IP}, A_{FC}, A_{IDB}, A_{CM}, A_{KB}, A_{DS}, A_{UI} \right),$$

where A_{IP} – agent of input and preprocessing of sound information, A_{FC} – *f*iltering and classification agent, A_{IDB} – agent working with data base of sound information, A_{CM} – conceptual modeling agent, A_{KB} – agent working with knowledge base of sound information classification, A_{SD} – agent for of decision support (DS) making about sound situation, A_{UI} – agent of user interface. In general, this model works including several algorithms. In the following, the main ones will be discussed.

The first algorithm starts from work of many agents A_{IP} which input and collect local sound information in some region and send it to the A_{FC} agent which will also get information from the A_{CM} agent and then send it to the agent A_{DS}. It works with agents A_{IDB}, A_{KB}, A_{UI} (data and knowledge bases, DS and user interface). The second algorithm have the same cycle as the first one, but in this case if there is some sound information missing so the A_{DS} agent will get back to the A_{IP} agent to get necessary information, and then the cycle will complete as the first one to get a better result.

The third algorithm is: before the A_{CM} agent give information to the A_{FC} agent it will communicate with the A_{IP} agent and get the required information.

More details of working these agents will be writing in further author publications.

MAS Structure for CPSI

The structure of multi-agent system for Collection and Processing Sound Information (CPSI) is composed of several different components that works together to collect sounds from the environment to get a required output (Fig. 1). These components can be classified in two parts. The first part is detecting and collecting sounds processors from the environment (A_{IP} model agents), while the other part is software-hardware realization on Server (A_{FC}, A_{IDB}, A_{CM}, A_{KB}, A_{DS}, A_{UI} model agents).

The detecting or collecting processor is composed of detectors or sound sensors (SD) so that the number of detectors will take in to consideration the zone or place that will be covered so that we will insure that we collect all the sound waves from a specified environment or zone.

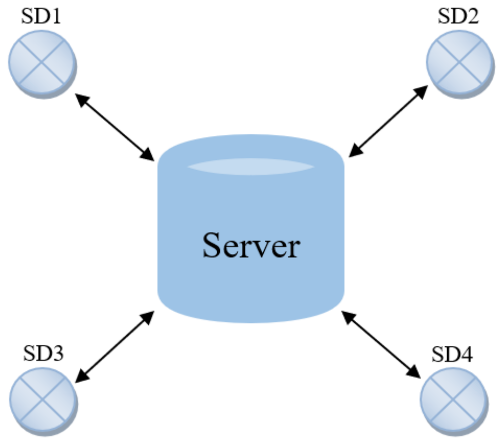

Fig. 1. MAS for Collection and Processing Sound Information (CPSI)

These sensors (SD) will be connected to the Server by the usage of wireless connection, so that we will have the flexibility to relocate the sensors depending on the zone that it is necessary to cover, and at the same time to insure that these detectors can be dynamic detectors not static, and also be flexible with different types of environment.

These components of MAS CPSI realize the model special algorithms which were given above. Common algorithm of MAS will allow specialist to select a specific sound length or sound range. If user wants to collect not only this but also avoid duplication in sound collecting so that if two or more detectors (SD) collect the same sound source from the environment and send it to the Server, it will drop all the common sound waves to decrease the data that will be studied and select the most clear data that was collected with the help of special methods and sensors that are provided by the second part of these agents as shown at Fig. 1.

Conclusion

Authors present the model and structure of MAS for CPSI. As a perspective of this work one will focus on each agent and will do each component of hardware-software implementation, a solution that would be practical for the end user. The detailed plan includes:

1. To create a hierarchy for conceptual representation and a complete set of pictograms to cover all noise types of sound.

2. In the transformation agent will focus on decision tree creation in order to swap between scales.

3. To regard the specific types of sound different types of detectors will propose the suggestion for the related sound detectors.

4. The last will be used as GUI graphical user interface that create automatic report for the end user.

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