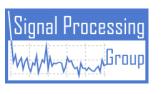


Adding Audio Capabilities to TIAGo Service Robot

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This work was supported by two grants of the Romanian National Authority for Scientific Research and Innovation, CNCS/CCCDI-UEFISCDI: partially by project number PNIIIP2-2.1-BG-2016-0378, 54BG/2016, and partially by project number PNIII-P2-2.1-PED-2016-1608, 222PED/2017, within PNCDI III.



Outline

- Research Aim
- >Who is TIAGo?
- Acquisition and Processing
- >Database
- >Features Extraction
- >Classification
- >Results
- >Conclusion



Research Aim

- To solve the problem of context awareness based on acoustic analysis for the service robot TIAGo, from PAL Robotics
- Service or social robots that share a space with people require the capacity to detect and track humans and recognize their activities
- Nowadays camera hardware and computer algorithms allow robots to process visual data from the world
 - Unfortunately, computer vision
 - > Is not the cheapest solution
 - > Needs a lot of information to be processed
 - > Depends on the ambient lightning
 - > Cannot detect information behind the scene \Rightarrow doesn't detect what is happening after some obstacles
 - This might be crucial for some human activities



Research Aim

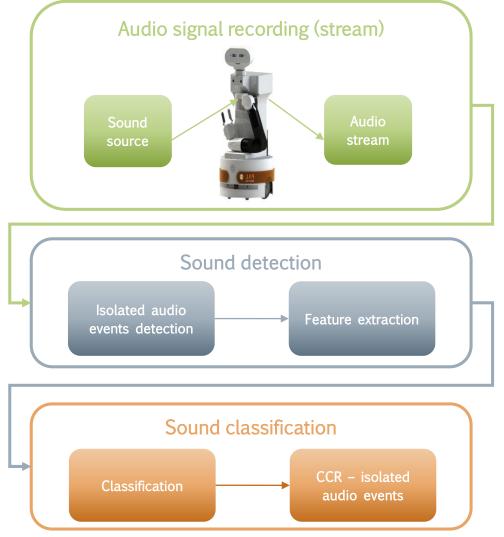
- > Audio appears to be a well suited sensory modality for this task
 - Since many human activities produce very characteristic sounds from which a robot can infer the corresponding human actions
- Sound environment analysis is an important, complementary simpler mean, compared to vision
 - Can help the robot to achieve a good understanding of the context
- For example, during the interaction with the human user the robot will be aware of the activities the human is involved into, i.e. walking, sleeping and talking
- The robot should at all times be aware of the environment in the house



- > TIAGo is a service robot designed to work in indoor environments
- People interested especially on ambient assisted living or in some easy tasks from industry can find TIAGo a suitable platform to develop their applications
- He combines mobility, perception, manipulation and human-robot interaction abilities
- Yet, researches on TIAGo have not been focused extensively on audio applications
- In this work we have presented how TIAGo's capabilities can be extended in such a way that he might handle tasks received through audio signals



Acquisition and Processing

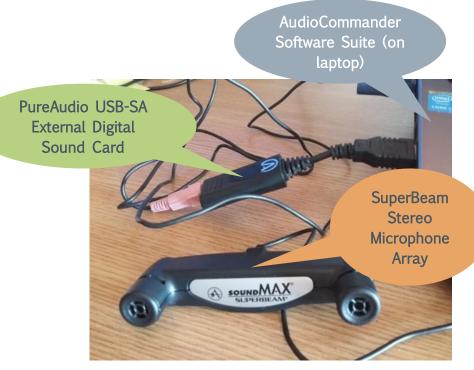


- Main purpose: to recognize isolated audio events that can occur in the environment in a home
 - Short duration (0.55
 ÷ 3.7 s), as a result of events such as
 - opening/closing of the microwave oven door
 - fall of an object on the floor
 - > hand clap
 - opening/closing of a door with the key, etc.



Sounds Acquisition

- The audio signals were recorded with both the TIAGo robot and the simulated TIAGo robot
- > The robot was simulated with a 2-microphone array connected to a laptop, identical to the robot one



- There was no difference between the two types of signals
- The USB-SA Array Microphone offers a USB digital sound card with a stereo array microphone for Andrea AudioCommander's
 - enhancement software
- The USB-SA external sound card eliminates computer noise floor problems



- The audio data stream was recorded to contain only a certain class of sound events
 - It was subsequently split into signals containing only one acoustic event
 - Except to time-domain isolation of the sound event, no post-processing such as noise elimination or normalization has been performed
- The recorded sound events were chosen to belong to the home environment



TIAGo Database

Kitchen	(8)
---------	-----

•chair

tap water
drop water
shower water
porcelain dish
cutlery
plastic bag rush
cardboard drop

> 1380 audio events

- 5 scenarios

- 46 sound classes

- 30 sounds/class

- 48 kHz, 16-bit accuracy

Room (8)

page turn
Velcro
zip open
zip close
door knock
door key
door open
door close

Appliances (5)
•washing machine •microwave open

- •microwave close
- •microwave alar
- •toaster alarm

	(5)	
nine ben ose arm	 hand clap finger clap cough laugh whistle 	

Non-verbal

Voice (20)

- •5 •6 •7
- •/

•1

•2

•3

•4

- •9
- •10
- •salut (hello)
- •medicamente (medicines)
- •da (yes)
- •nu (no)
- •dreapta (right)
- •stanga (left)
- •stai (stay)
- •vino (come)
- •du-te (go)
- •TIAGo



Features Extraction

- > Frames: 25 ms + 60% overlap
- > Features vector Read audio file k $- LPC: \mathbf{A}_{k} = \begin{bmatrix} \sigma_{k}^{2} & a_{k,1} & a_{k,2} & \dots & a_{k,p} \end{bmatrix}$ *k* = 1:1380 σ_k^2 – prediction error variance $a_{k,i}$ – last p LPC coefficients Extract features $- LPCC: \mathbf{A}_{k} = \begin{bmatrix} \ln \sigma_{k}^{2} & c_{k,1} & c_{k,2} & \dots & c_{k,p} \end{bmatrix}$ > $c_{k,i}$ – LPCC coefficients computed based on σ_k^2 .mat $-MFCC: \mathbf{A}_{k} = \begin{bmatrix} E_{k} & C_{k,1} & C_{k,2} & \dots & C_{k,p} \end{bmatrix}$ > E_k – signal energy > $C_{k,i}$ – MFCC coefficients Convert .mat 2 .arff > Features matrices $\mathbf{F}_{1380\times(p+1)} =$
 - > p = 10:2:38 orders for the prediction filter (LPC, LPCC) / number of cepstral coefficients (MFCC)

MATLAB®



Classification



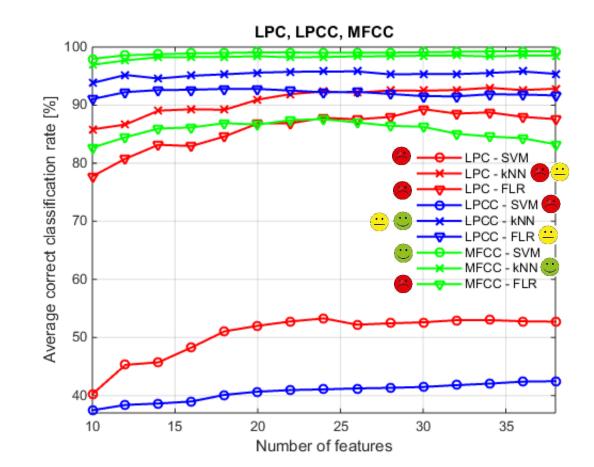
>WEKA - 8 classifiers

- Open source software issued under the GNU General Public License
- A collection of machine learning algorithms for data mining tasks
- Tools for data pre-processing, classification, regression, clustering, association rules, and even visualization
 - 1) Bayesian Network (BN)
 - 2) Quadratic Discriminant Analysis (QDA)
 - 3) Support Vector Machines (SVM)
 - 4) Multilayer Perceptron (MLP)
 - 5) k-Nearest Neighbor (kNN)
 - 6) KStar
 - 7) Fuzzy Lattice Resoning (FLR)
 - 8) Random Forests (RF)



Results

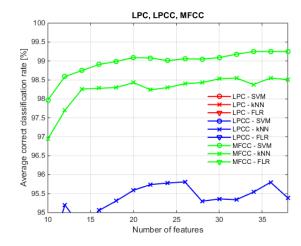
> The results obtained represent the average of the 10 runs (100 experiments/classifier) for each classifier





Results

- For audio signal detection problems we need a high CCR and a low Std.Dev.
- > Only MFCC fulfil the requirements
 - The highest CCR and lowest Std.Dev.
 - > SVM and kNN classifiers
 - > CCR is greater than 96.5%



- In order to obtain a CCR greater than 99% we need at least 21 characteristics for SVM
- To improve the accuracy of the classification, a grid search algorithm was applied to SVM, and in the case of kNN the optimal value for k was searched



Real Life Scenario

- > We split the data from each class into
 - Training data (2/3)
 - Testing data (1/3)
 - -SVM CCR[%] (Std.Dev.)

	Features	Iraining	lesting
	MFCC-20	100 (0.08)	99.35 (0.06)
	MFCC-22	100 (0.09)	99.13 (0.05)
	MFCC-24	100 (0.09)	99.35 (0.06)
Dataset_Train Class Training Set	MFCC-26	100 (0.08)	99.35 (0.06)
Test = 1/3	MFCC-28	100 (0.09)	99.35 (0.06)
data Set dat	MFCC-30	100 (0.11)	99.35 (0.06)
Dataset_Test Class Test SetMaker	MFCC-32	100 (0.11)	99.35 (0.05)
Model Performance Chart	MFCC-34	100 (0.11)	99.35 (0.06)
	MFCC-36	100 (0.11)	99.35 (0.06)
	MFCC-38	100 (0.11)	99.35 (0.05)



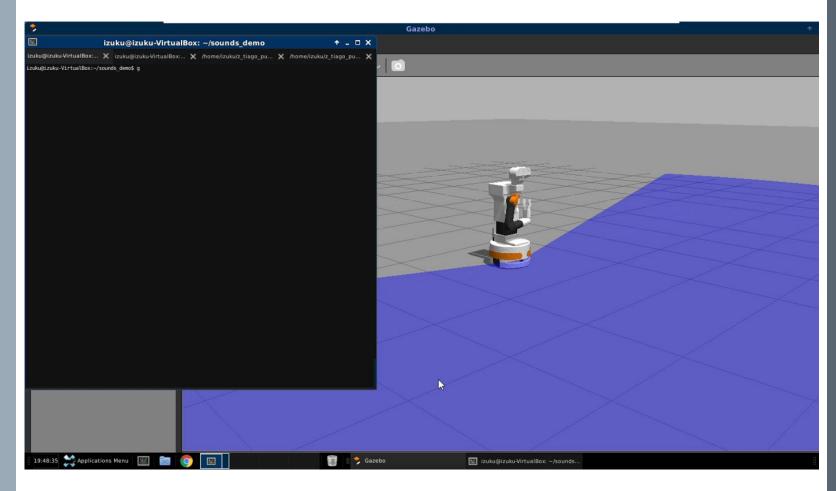
Conclusion

- > We have shown how the capabilities of the TIAGo robot can be extended in such a way that it might handle tasks received through audio signals
- The audio data stream was recorded to contain only a certain class of sound events and a total of 30 audio signals were obtained for each 46 classes
- > For each audio signal, three types of features have been extracted: LPC, LPCC, and MFCC
- From the 8 tested classifiers, the best results were obtained for SVM, kNN and FLR
- On the features extraction side, it is best to use the MFCC coefficients
- > As a classifier, either SVM or kNN can be used in terms of credibility, specialized literature and computation time



Demo

> Gazebo simulator

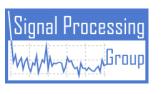


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