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Emotion and Gender Recognition of Speech Signals Using SVM

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Abstract- In the present day speech signal processing has a very wide range of applications in many technical fields like human computer interaction, biometrics, artificial intelligence etc. In speech processing emotion recognition is major research area where different emotions of people are recognized In this paper the proposed system allows recognizing a person's emotional state from audio signals. The proposed solution is aimed at improving the interaction among humans and computers, thus allowing effective human-computer intelligent interaction. The system is able to recognize six emotions (anger, boredom, disgust, fear, happiness and sadness). This set of emotional states is widely used for emotion recognition purposes. It also distinguishes a single emotion versus all the other possible ones, as proven in the proposed numerical results. The system is composed of two subsystems namely Emotion recognition (ER)&Gender recognition (GR). For this two support vector machines (SVM'S)are used for the male and female speaker's emotion recognition. The experimental analysis shows the performance in terms of accuracy of the proposed ER system. The results highlight that the a priori knowledge of the speaker's gender allows a performance increase. The obtained results also show that the features selection adoption assures a satisfying recognition rate and allows reducing the employed features.

Index Terms—**emotion recognition, Gender recognition, Human-computer interaction, Support Vector Machine.**

I. INTRODUCTION

Recently there has been growing interest to improveHuman-computer interaction (HCI) means computers should interact to the humans in day to day life .**In this context recognizing people emotional state and givingsuitable feedback may play a crucial role** [1]. As a consequence, emotion recognition represents a hot research area in both industry and academic field. Usually emotion recognition based on facial or voice features. This paper proposes a solution, designed to be employed in a smart phone Environment able to capture emotional state of a person starting from registration of speech signals in the surrounding obtained by mobile devices such as smartphones[2],[3].

This paper presents the implementation of a voice-based emotion detection system which is suitable to recognize six emotions (anger, disgust, fear, happiness, sadness, surprise) as widely used for emotion recognition. Particular attention is also reserved to the evaluation of the system capability to recognize the single emotion with and without Gender recognition (GR); .**The classification task for speech signals is done by using Support Vector Machine (SVM) approach.**

The main contributions of this paper concern: *i)* a system able to recognize people emotions composed of two sub-systems, Gender Recognition (GR) and Emotion Recognition (ER); gender recognition algorithm, based on pitch extraction, and aimed at providing *a priori* information about the gender of the speaker; SVM-based emotion classifier, which employs the gender information as input. Reduced feature sets, obtained by feature selection, performed through Principal Component Analysis (PCA), have been investigated and applied. In order to train and test the mentioned SVM-based emotion classifier, a widely used emotional database called (Enterface database ED) has been employed.

Experimental results show that the proposed system is able to recognize the emotional state of a speaker with an accuracy level often higher than the evaluated methods taken from the literature, without applying any pre-processing on the analysed speech signals. The obtained results show also that adopting a feature selection algorithm assures good recognition rate levels also when a consistent reduction of the used features is applied. Thisallow a strong limitation of the number of operations required to identify the emotional content of a particular audio signal.

The obtained results also show a strong dependency of the overall system reliability on the database adopted for training and testing phases: the use of a simulated database (i.e., a collection of emotion vocal expressions played by actors) allows obtaining a higher level of correctly identified emotions. In addition, the performed

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tests show that the SVM-based emotion classifier can be reliably used in applications where the identification of a single emotion (or emotion category) versus all the other possible ones is required, as in case of panic or annoyance detection. The proposed method based on the employment of audio signals consists of four principal parts which are elaborated bellow

A. FEATURES SELECTION

Many different speech feature extraction methods have been proposed over the years. Methods are distinguished by the ability to use information about human auditory processing and perception, by the robustness to distortions, and by the length of the observation window. Due to the physiology of the human vocal tract, human speech is highly redundant and has several speaker-dependent features, such as pitch, speaking rate and accent. An important issue in the design of a speech emotion recognition system is the extraction of suit-able features that efficiently characterize different emotions. Although there are many interesting works about automatic speech emotion detection [8] there is not a silver bullet feature for this aim.

Since speech signal is not stationary, it is very common to divide the signal in short segments called frames, within which speech signal can be considered as stationary. Human voice can be considered as a stationary process for intervals of 20 40 (ms). If a feature is computed at each frame is called local, otherwise, if it is calculated on the entire speech is named global. There is not agreement in the scientific community on which between local and global features are more suitable for speech emotion recognition.

1) GENDER RECOGNITION FEATURES

Together with the Mel Frequency Cepstral Coefficients (MFCC) [7] pitch is the most frequently used feature since it is a physiologically distinctive trait of a speaker's gender. Other employed features are formant frequencies and bandwidths, open quotient and source spectral tilt correlates energy between adjacent formants, fractal dimension and fractal dimension complexity jitter and shimmer (pitch and amplitude micro-variations, respectively) harmonics-to-noise-ratio, distance between signal spectrum and formants.

2) EMOTION RECOGNITION FEATURES

Coherently with the wide literature in the field, in this paper a set of 182 features has been analysed for each the recorded speech signal, including: Mean, variance, median, minimum, maximum and range of the amplitude of the speech Mean, variance, minimum, maximum and range of the formants; Energy of the Bark sub-bands Mean, variance, minimum, maximum and range of the Mel-Frequency Cepstrum Coefficients Spectrum shape features Centre of Gravity, Standard Deviation, Skewness and Kurtosis; Mean and standard deviation of the glottal pulse period, jitter local absolute, relative average perturbation, difference of difference period and (–ve) point period perturbation quotient.

B. FEATURE SELECTION REDUCTION

A crucial problem for all emotion recognition systems is the selection of the best set of features to characterize the speech signal. The purpose of this part is to appropriately select a subset of features from the original set in order to optimize the classification time and the accuracy. In the case of real-time applications reducing the number of used feature is crucial in order to limit the computational complexity and the required time to complete the emotion recognition process. An increase in classification performance usually would be expected when more features are used. Nevertheless, the performance can decrease for an increasing number offeatures if the number of patterns is too small. This phenomenon is known as the curse of dimensionality. This part also aims at reducing the speech features set size either by selecting the most relevant feature subset and removing the irrelevant ones or by generating few new features that contain most valuable speech information. The most per formant strategy to get the best features set is an exhaustive search but it is often computationally impractical. Therefore, many sub-optimum algorithms have been proposed.

C. DATABASE

There are many databases that are used for the speech signal analysis such as Berlin Emotional database (BED) Reading-Leeds database, Belfast's database [5], expressive speech database. Here in this paper enterface database is used it is an English language database as English is an universally known language we adopted that database .and it is easy to compute.

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D. CLASIFICATION

It assigns a label representing the recognized emotion by using the features selected by the Feature Selection block and the sentences in the Database we have used Support Vector Machine(SVM) as a classifier .There are many classifiers such as K-fold classifier, Artificial Neural Networks(ANN), KNN nearest neighbour each one having their own advantages and drawbacks but when we are talking of the speech signals which are non-stationary SVM yields good results and the experimental results also prove it .

II. EMOTION AND GENDER RECOGNITION SUBSYSTEM

The system is aimed at resigning six universal emotions (anger, disgust, fear, happy, sad, surprise) .The overall system is shown as

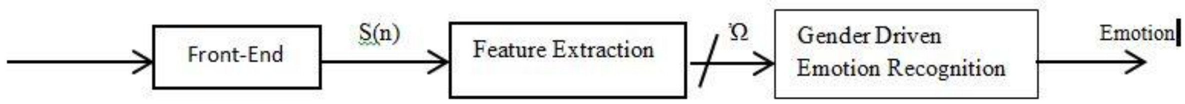

Fig1: indicates emotion recognition system architecture [12]

The quantity $s(t)$ represents the original continuous input audio signal. The Front-End block acquires $s(t)$ and samples it with frequency F_S D 16 [KHz] in order to obtain the discrete sequence $s(n)$. After this step, a feature vector • is computed by the Features Extraction block. It is worth noticing that • includes the features Ώ •^{GR} and Ώ•^{ER} respectively employed by the Gender Recognition and the Emotion Recognition Subsystems. In practice the feature vector may be written asΏ= [Ώ•^{GR};Ώ •^{ER}]. Ώ is employed by the Gender-driven Emotion Recognition block that provides the output of the overall process: the recognized emotion. As already said and discussed in the reminder of this Section, this block is divided into two subsystems: Gender Recognition (GR) and Emotion Recognition (ER).

GENDER RECOGNITION ALGORITHM

The proposed GR method is designed to distinguish a male from a female speaker. For this the chosen feature is the mean of the Probability Density Function (PDF), whose definition is of a number of frames of the voice signal, as explained below. The signal to be classified as ``Male" or ``Female" is identified as $s(n)$, n= 1 …… N.The GR method introduced in this paper is composed of the following steps:

1) The signal$s(n)$ is divided into frames.
2) The pitch frequency for each frame is estimated.
3) A number of frames of$s(n)$ is grouped into an odd-number of blocks.
4) The pitch PDF is estimated for each block.
5) The mean of each pitch PDF (PDF_{mean}) is computed.
6) The decision about ``Male" or ``Female" is taken, for each block, by comparing their PDF_{mean} with a threshold $_{thr}$ computed by using the training set.

The final decision on the whole signal gender is taken by the majority rule: the signal $s(n)$ is classified as ``Male" if the majority of its blocks are classified as ``Male". Otherwise, it is classified as ``Female"

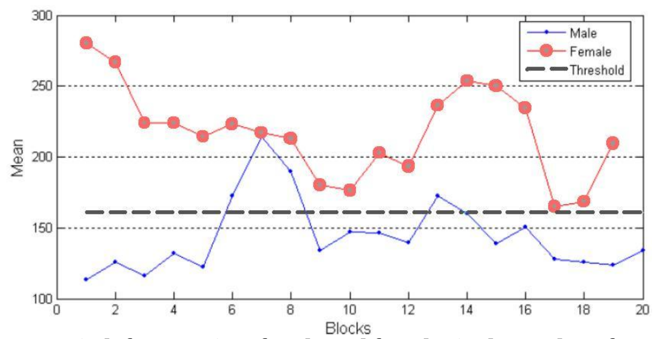

Fig 2: Represents average pitch frequencies of male and female single speakers for 20 blocks[12]

The proposed GR method has a very low computational complexity and therefore consumes a limited quantity

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of energy, nevertheless it guarantees 100% recognition performance, as the solutions proposed in[4]and[5] .The reminder of this section is focused on the detailed description of the single steps followed by the GR algorithm.

PITCH FREQUENCY ESTIMATION

Speech signal exhibits a relative periodicity and its fundamental frequency, called pitch (frequency), is usually the lowest frequency component [6]. In the case of this paper, it is important to estimate the Probability Density Function (PDF) of the pitch of a given speech signal. The applied procedure applied will be described in the following subsection. In general, for voice speech, pitch is usually defined as the rate of vibration of the vocal folds [9] and for this reason, can be considered a distinctive feature of an individual. Estimating the pitch of an audio sample could therefore help classify it as belonging to either a male or a female, since its value for male speakers is usually lower than the one for female speakers. Many pitch estimation algorithms have been proposed in the past years, involving both time- and frequency-domain analysis .Many developed methods are context specific, but pitch estimators designed for a particular application depend In particular, given a real-value discrete-time signal *s*(*n*), *n* €[1…….*N*]

$$\sum_{n=0}^{N-1} s(n)s(n+\tau) \quad \tau\epsilon[0,1,\ldots.N] \quad (1)$$

Where R(τ) is auto-corelation function Here the values are taken as

$$\tau_1 = \left[F\frac{s}{P_2}\right] \text{and } \tau_2 = [F\frac{s}{P_1}] \qquad (2)$$

$F_s$is the sampling frequency applied to the original analoguesignal to obtain the discrete-time signal *s*(*n*). In practice, the applied autocorrelation is defined in (3)

$$R^{\wedge}(\tau) = \sum_{n=0}^{N-1-\tau} s(n)s(n+\tau) \quad (3)$$

By these the pitch period can be obtained from the speech samples as

$$\tau = arg_{\tau}\, maxR^{\wedge}(\tau)(4)$$

The frequency of the pitch is computed as

$$P_{pitch} = \frac{F_s}{\tau_{pitch}} \qquad (5)$$

PDF ESTIMATION

The probability density function has to be estimated and it can be estimated by employing bellow equation

$$PDF_{(P)}(P)=\sum_{h-0}^{H-1} w_h.rect\left(\frac{P-[\frac{1}{2}+h)\Delta P]}{\Delta P}\right) \quad (6)$$

GENDER CLASIFICATION

In order to determine the best feature vector Ω^{GR} that maximizes the efficiency of the proposed GR method, different feature vectors were evaluated by combining different individual features:

.PDF maximum: PDF_{max}

.PDF mean: PDF_{mean}

PDF standard deviation: PDF_{std}; PDF roll-off:

By using a general set of features, the feature vector for each block is composed of the equation bellow

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$$\Omega^{GR} = \{\omega_1{}^{GR}, \ldots \omega_2{}^{GR}, \ldots . \omega_Z{}^{GR}\} \quad (7)$$

EMOTION RECOGNITION (ER) SUBSYSTEM

The implemented Emotion Recognition (ER) subsystem is based on two inputs: the features extracted by the Features Extraction Block, in particular the sub-set Ω^{ER} of features needed for the emotion recognition and the recognized speaker gender provided by the GR subsystem. Differently from the GR subsystem in which the employed feature has been individuated (the Pitch), concerning the ER subsystem the selection of feature(s) to be employed is still an open issue. For this reason, this paper does not provide a set of features but proposes a study that takes into account the most important features employed in the literature and their selection through a features selection algorithm. Indeed, the features employed in the ER subsystem are based on a set of features or on a sub-set of them. Sub-sets have been individuated by using a ***Principal ComponentAnalysis***(PCA) algorithm and have been evaluated in termsof recognition rate. The recognition rate obtained by varying the selected features

CLASSIFICATION

Usually, in the literature of the field, a Support VectorMachine (SVM) is used to classify sentences. SVM is a relativelynew machine learning algorithm introduced by Vapnik[11] and derived from statistical learning theory in the 90s.The main idea is to transform the original input set into a highdimensionalfeature space by using a kernel function andthen, to achieve optimum classification in this new featurespace, where a clear separation among features obtained bythe optimal placement of a separation hyperplane under theprecondition of linear reparability.Differently from the previously proposed approachestwo different classifiers, both kernel-based Support VectorMachines (SVMs), have been employed in this paper

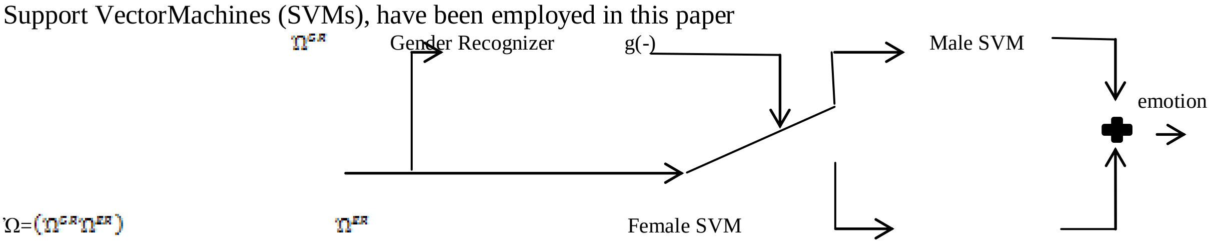

FIG 3: Emotion Recognition (ER) subsystem [12].

The first one (called Male-SVM) is used if a male speaker is recognized by the Gender Recognition block. The other SVM (Female-SVM) is employed in case of female speaker. Male-SVM and Female-SVM classifiers have been trained by using speech signals of the employed reference Data Base (DB) generated, respectively, by male and female speakers. Being g = [1; 1] the label of the gender, the two SVMs have been trained by the traditional Quadratic Programming (QP) as done. In more detail, the following problem has been solved for each gender

PERFORMANCE EVALUATION

In this Section the performance evaluation of the overall Emotion Recognition (ER), in terms of accuracy (i.e., correct detection rate), of the system is presented. The recognized emotions are: anger (AN), surprise (SU), disgust (DI), fear (FE), happiness (HA), sadness (SA), together .The reported results are divided into two main parts. The first part shows the performance of the system if no information about the gender of the speaker is exploited in the emotion recognition process. The second part of the results provides the performance obtained by exploiting the knowledge related to the speakers' gender. The experimental results highlight that the gender information allows incrementing the accuracy of the emotion recognition system on average.

WITHOUT GENDER RECOGNITION

In this subsection, the accuracy of a traditional approach, without having any ``*a priori*'' information on the gender of the speaker, is shown. In this case, a single SVM has been trained with both male and female speeches. In more detail, the SVM has been trained and tested, considering the overall BES signals, by the *k*-fold cross-validation approach. The original BES signals are randomly partitioned into *k* equal size subsets. Among the *k* subsets, a single subset is retained to test the SVM, and the other *k* 1 subsets are employed to train it. The cross-validation process is then repeated *k* times, with each of the *k* subsets used once as validation set. The obtained *k* results are then averaged to produce a single result. In this paper, in all considered cases, *k* D 10

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has been employed.

WITH GENDER RECOGNITION

Differently from the previous Section, now we evaluate the system performance when the ``*a priori*'' information on the gender of the speaker is used. This information has been obtained by exploiting, in the testing phase, the Gen-der Recognition subsystemand providing 100% gender recognition. In this case, as depicted in Fig. 3 and as extensively explained before, two SVMs, one for each gender, have been trained: the first SVM through male speeches signals, the second through female ones. Also in this case, SVM training and testing phases have been carried out by two *k*-fold (*k* D 10) cross-validations and, again, the overall ED signals have been employed by dividing male speech from female speech signals.

Reported results show that the employment of information related to speaker gender allows improving the performance. The overall set of features has been employed for these tests. In more detail, and Table show the confusion matrices concerning male and female speech signals, respectively.

EMOTIONS RECOGNIZED	TIME ELAPSED FOR RECOGNITION(ms)	
	Without GR	**With GR**
ANGER	69.699	73.3801
DISGUST	68.4238	43.8991
FEAR	117.1501	76.1518
HAPPY	75.6779	44.1407
SAD	101.9759	77.5666
SURPRISE	50.6985	45.0014

Table1: represents time elapsed for different emotions with and without Gender Recognizer (GR).

RESULITS AFTER SIMULATION

The results after simulation were shown in a graph as we discussed earlier the accuracy rate when gender recognition module was included was increased heavily the results shown in the above table were noted for speech samples of 31 .Higher recognition rate can be obtained if you give more training to your classifier

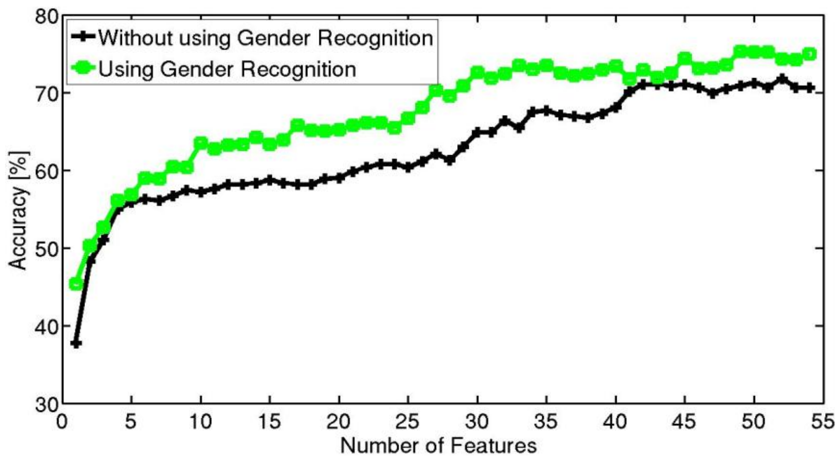

FIG 4. Recognition Percentage of the ER system versus the number of selected features [12].

SINGLE EMOTION DETECTION

In some applicative scenarios the recognition of a specific emotion with respect to the others is of great interest. For example, Safety and Security applications, which must recognize dangerous events in critical areas, such as train stations and airports, can exploit the recognition of fear detected by several smartphones users in the same

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zone to automatically monitor the whole area. Another possible example may concern Entertainment applications aimed at monitoring the positive opinion about plays, movies, concerts and shows: in all these cases the recognition of happiness among the other emotions can be a useful feedback. For this reason, the proposed approach, which employs the gender information, has been compared, in terms of accuracy, with the traditional approach, which does not employ such information, to discriminate a particular emotion among all the other the figures show single emotion detection (vs) single emotion detection.

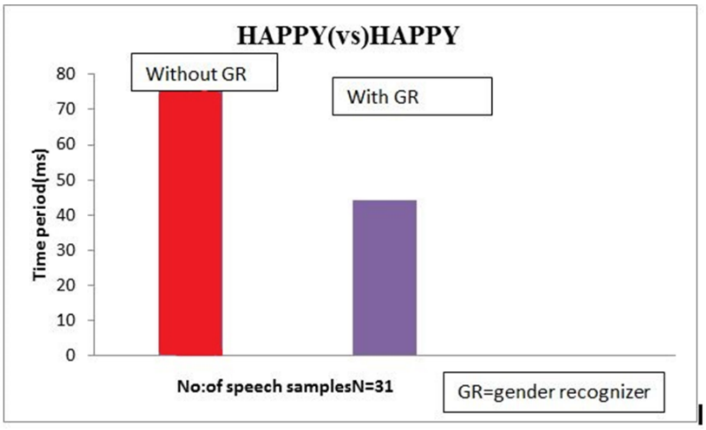

Fig5:happy (vs)happy

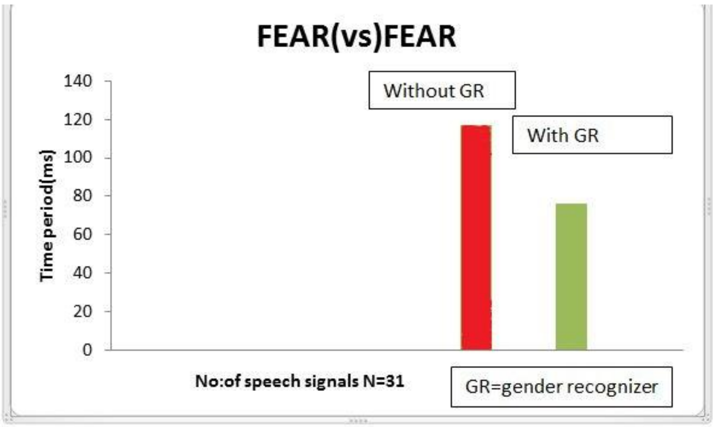

Fig6: fear (vs)fear

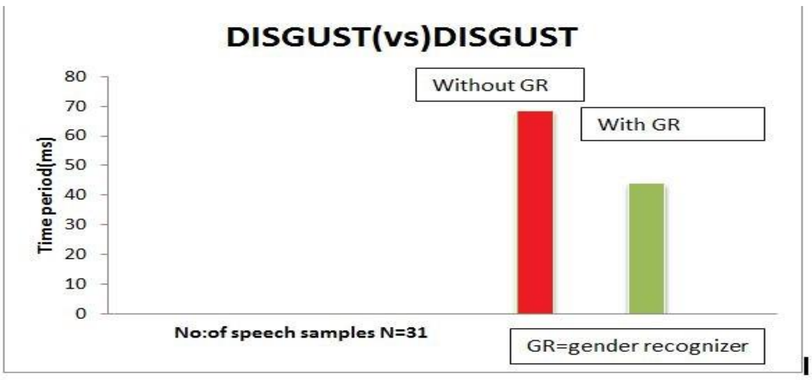

Fig7: disgust (vs)disgust

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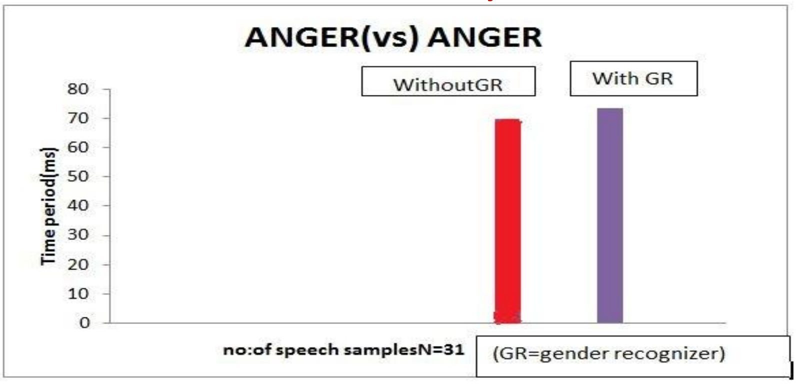

Fig8: anger (vs)anger

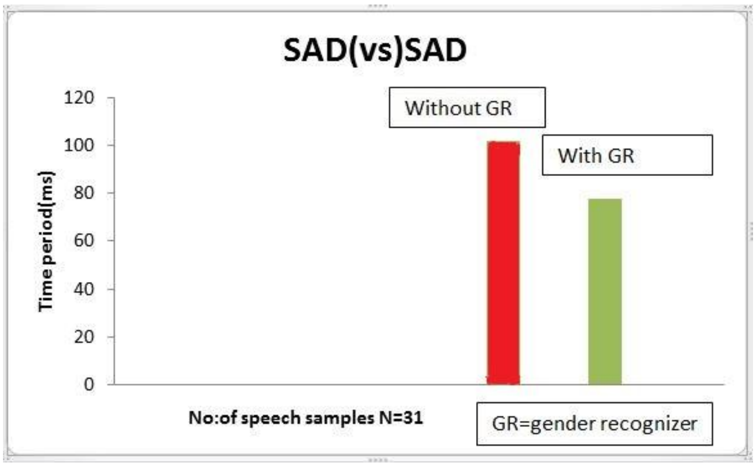

Fig9:sad(vs)sad

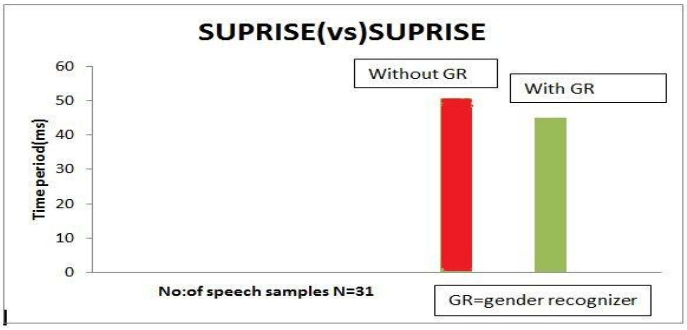

Fig10:surprise(vs)surprise

III. CONCLUSION

The proposed system, able to recognize the emotional state of a person starting from audio signals registrations, is com-posed of two functional blocks: Gender Recognition (GR) and Emotion Recognition (ER). The former has been implemented by a Pitch Frequency Estimation method, the latter by two Support Vector Machine (SVM) classifiers (fed by properly selected audio features), which exploit the GR subsystem output.

The performance analysis shows the accuracy obtained with the adopted emotion recognition system in terms of recognition rate and the percentage of correctly recognized emotional contents. The experimental results highlight that the Gender Recognition (GR) subsystem allows increasing the overall emotion recognition accuracy from 80.4% to 84.5% due to the *a priori* knowledge of the speaker gender.

The results show that with the employment of a features selection algorithm, a satisfying recognition rate level can still be obtained also reducing the employed features and, as a con-sequence, the number of operations required to identify the emotional contents. This makes feasible future development of the proposed solution over mobile devices.

The obtained results underline that our system can be reliably used to identify a single emotion, or emotion category, versus all the other possible ones.Possible future developments of this work can follow different directions: *i)* evaluation of the system performance by grouping the considered emotions in bigger sets (i.e., negative (vs) positive emotions); *ii)* evaluation of different classification algorithms; *iii)* implementation and related performance investigation of the proposed system on mobile devices; *iv)* computational load and energy consumption analysis of the implemented system.

IV. FUTURE SCOPE

This paper presents the implementation of a voice based emotion detection system it presents an opportunity to implement it over smart phone platforms. In future it can be used in smart home, smart office and virtual reality, and it may acquire importance in all aspects of future people’s life.

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