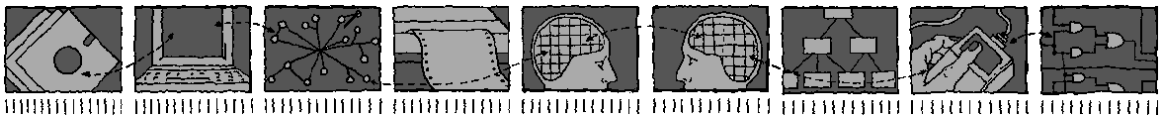
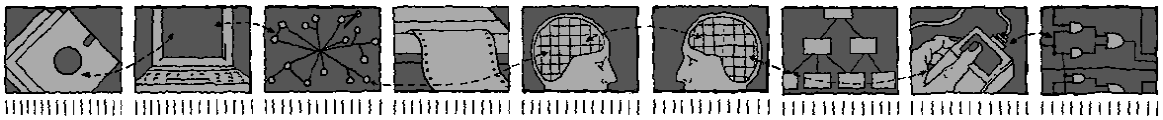


Department of Computing Science and Mathematics
University of Stirling



Cognitively Inspired Fuzzy Based Audiovisual Speech Filtering

Andrew K. Abel, Amir Hussain

Technical Report CSM-198

ISSN 1460-9673

April 2014

Department of Computing Science and Mathematics
University of Stirling

Cognitively Inspired Fuzzy Based Audiovisual Speech Filtering

Andrew K. Abel, Amir Hussain

Department of Computing Science and Mathematics
University of Stirling
Stirling FK9 4LA, Scotland

Telephone +44 1786 467 421, Facsimile +44 1786 464 551
Email aka@cs.stir.ac.uk

Technical Report CSM-198

ISSN 1460-9673

April 2014

Abstract

In recent years, the established link between the various human communication production domains has become more widely utilised in the field of speech processing. Work by the authors and others has demonstrated that intelligently integrated audio and visual information can have a vital role to play in speech enhancement. Of particular interest to our work is the potential use of visual information in future designs of hearing aid and listening device technology. A novel two-stage speech enhancement system, making use of audio only beamforming, automatic lip tracking, and visually derived speech filtering, was initially developed by the authors and its potential evaluated in a previous paper. This work found that the use of visual information was of benefit in some scenarios, but not all. In addition to the use of visual information based on the concept of lip-reading, there is also scope for the development of cognitively inspired speech processing approaches that function in a similar manner to the multimodal attention switching nature of the human mind. One example of this is the use of the visual modality for speech filtering in only the most appropriate environments (such as when there is a lot of background noise, and when the visual information is of a suitable quality to be used). This cognitively inspired approach ensures that visual information is only used when it is expected to improve performance. It is also worth considering the possibility of environments where multimodal information may be sporadic and of varying quality. One single speech filtering approach may produce inadequate results when applied to a wide range of environments. To alleviate this, we present a cognitively inspired fuzzy logic based multi-modal speech filtering system that considers audio noise level (using a similar manner to level detectors used in conventional hearing aids) and evaluates the visual signal quality in order to carry out more intelligent, automated, speech filtering. These detectors are used as part of a fuzzy logic based system to determine the optimal speech filtering solution for each frame of speech. When tested with a wide variety of challenging data, the results show that a nuanced approach is capable of automatically switching between approaches when considered appropriate. The proposed approach is intended to be a cognitively inspired scalable, adaptable framework, with promising initial results.

Acknowledgements

This work was funded by a University of Stirling PhD scholarship, with additional work carried out with the aid of an EPSRC grant (EP/G062609/1). The authors would also like to thank Leslie Smith of the University of Stirling for his assistance and guidance with preparing this report. We are also very grateful for the support and advice over the years provided by others, particularly participants and organisers of the COST Action 2102, Cross-Modal Analysis of Verbal and Non-verbal Communication.

Contents

List of Figures

List of Tables

1 Introduction

The multimodal nature of both human speech production and perception is well established. The relationship between audio and visual aspects of speech has been investigated in the literature, demonstrating that speech acoustics can be estimated using visual information. This information has become relevant to the field of speech enhancement in recent years. This is a very active field of research, with a number of practical applications, such as improved hearing aids [2] or better surveillance equipment. In recent decades, many different audio-only speech enhancement solutions have been proposed, such as [3], [4], and [5].

1.1 Background

A common speech filtering technique is to use multiple microphone techniques such as beamforming that can improve speech quality and intelligibility by exploiting the spatial diversity of speech and noise sources [6], [7]. An alternative speech enhancement technique is to make use of Wiener filtering [8], which compares the noisy signal to an estimate of the noise free speech signal. There are also approaches such as that proposed by Zelinski [3] and refined by others, including [9], [10], and [11] that propose a two stage audio-only speech enhancement solution that makes use of both adaptive beamforming and Wiener filtering in a single integrated system. In real world applications where the noise and environment are not consistent, conventional single stage beamforming has practical limitations, and is the subject of much active research [5], [12]. Efforts have been made to solve this issue with the use of visual information [13], [14], [15], for aiding source separation, demonstrating that multimodal speech filtering is feasible.

The multimodal nature of both perception and production of human speech is well established. Speech is produced by the vibration of the vocal cords and the configuration of the vocal tract, which is composed of articulatory organs. Due to the visibility of some of these articulators (such as lips, teeth and the tongue), there is an inherent relationship between the acoustic and visible properties of speech production. The relationship between audio and visual aspects of speech perception has been established since pioneering work by Sumby and Pollack in 1954 [16], which demonstrated that lip reading improves the intelligibility of speech in noise when audiovisual perception is compared with equivalent audio-only perception. This was also confirmed by others [17], including in work by Summerfield in 1979 [18]. Classically, this work reports gains in the region of 10-15dB when compared to audio-only perception results [19]. This is further demonstrated by the well-known McGurk effect [20], which provides a physical demonstration of the relationship between hearing and vision in terms of speech perception. This cognitive link between audio and visual information is further demonstrated in work concerning audio and visual matching in infants by Patterson and Werker [21], [22]. This correlation between audio and visual modalities can also be seen in studies of primates [23].

Further confirming the cognitive links between modalities, it has been shown that speech is perceived to sound louder when the listener looks directly at the speaker [24], as if audio cues are visually enhanced [25]. In addition, work by researchers including Kim and Davis [26], and Bernstein et al. [27], has shown that visual information can improve the detection of speech in noise [28]. In addition to the gain in speech detection, work by Schwartz et al. [24] also investigated if visual cues present in speech information could produce a gain in intelligibility by using French vowels with very similar lip information and then dubbing different (but very similar) audio information over it. Despite the information not matching, a gain in intelligibility was identified when audiovisual information was used, suggesting that audio and visual information are integrated at a very early stage.

Studies have also shown that when informational masking (such as a competing speaker) is considered, visual information can have a dramatic effect, including research by Helfer and Freyman [29], and Wightman et al [30]. An additional detailed discussion of audiovisual speech perception is presented in [31], and a further detailed summary can be found in work by the authors in [1]. In addition, the correlation between audio and visual aspects of speech has been deeply investigated in the literature [32], [33], [34], and in work by the authors [35], [36], showing that facial measures provide enough information to reasonably estimate related speech acoustics.

The connection between modalities demonstrates the cognitive nature of hearing. The improvement found in perception and detection of speech when the visual information is involved, along with the multimodal illusion demonstrated by the McGurk effect, shows that the process of hearing involves cognitive influence. In addition, the switch in attention focus to use varying amounts of visual information depending on relevance, and also the use of visual cues shows that there is a significant degree of processing in the brain.

Since pioneering multimodal speech enhancement techniques proposed by Girin et al. [37], there has been much development in this field [38], [39]. Recent work has included research by Almajai et al. [40], who make use of visual information, phoneme based speech segmentation, and a Voice Activity Detector (VAD). The

system combines both visual and audio feature extraction, a multimodal VAD, a visually derived Wiener filtering approach, takes account of the level of noise when it comes to phoneme decoding, and filters the signal differently depending on the phoneme identified. The authors report good results, however there are some limitations to the work, such as being trained with a limited training set, the system as presented being strongly reliant on visual information, and not taking account of situations without suitable camera input (such as a moving source or light level changes). A recent paper by Abel and Hussain [1] presented a two stage speech enhancement approach that made use of visually derived Wiener filtering and beamforming. It was concluded that this approach could function effectively in several scenarios (such as extremely noisy environments with an SNR below -20dB), but did not perform well in all instances (such as when visual information is not available).

1.2 Contribution of this Paper

In this paper, we build on previous audiovisual speech processing work by the authors [36], [35] [1] to present a cognitively inspired multimodal speech filtering system, making use of both visual and audio information to enhance speech. A multistage speech enhancement system was previously presented by the authors [1], that combines both audio and visual information for speech filtering. In this system, noisy speech information received by a microphone array was first pre-processed by Wiener filtering; making use of matching visual speech information to estimate speech information using an audiovisual model (trained using offline information). This pre-processed speech is then enhanced further by audio beamforming using a state of the art general transfer function generalised sidelobe canceler (TFGSC) [6] approach.

The results presented in previous work showed the effectiveness of making use of visual information in environments with significant levels of background noise, but also identified some limitations with the performance of this approach. One such limitation was the use of visual information in scenarios when it was not considered to be suitable. This includes when visual information is not available (for example, due to movement of the speaker), or when it is considered to have a negative effect on speech filtering performance (such as in a higher SNR, as found by Abel and Hussain [1]). This paper presents a cognitively inspired approach that follows the attention switching model, where humans make intermittent use of visual information when available. To do this, our original speech filtering system presented in [1] is refined with the use of a fuzzy-logic system. With this system, the audio and visual information is extracted, and a number of fuzzy-logic detectors are then applied. These consist of a level detector, a previous frame output, and a visual quality detector. The detectors are used to determine the most suitable form of processing to utilise to filter individual frames of an input speech sentence, depending on the input fuzzy detectors.

To test this system, a corpus of challenging novel data has been recorded, and the results show that the level detectors function appropriately as part of a fuzzy logic system, and in turn, the fuzzy logic based cognitively inspired filtering is capable of switching between filtering methods correctly depending on environmental conditions. Some further limitations with the overall approach are then identified, as visually derived filtering produces poor filtering results when presented with completely novel data that does not resemble that which it has been trained with, and so while the switching results are positive, the resulting speech requires further improvement.

The remainder of this paper is divided up as follows. Section 2 summarises our previous two-stage audiovisual speech filtering system and the results previously presented in [1]. The justification and rationale behind the novel cognitively inspired fuzzy logic based system presented in this work is discussed in section 3, as well as a full description of the new system. The novel corpus recorded to test this work is described in section 4, and then results are presented in section 5. Limitations, strengths, and possible refinements are discussed in section 6, and finally, section 7 concludes this paper and briefly outlines future research directions.

2 Previous Research Findings

2.1 Previous Audiovisual System

This work makes use of a recently developed visual tracking technique [41], for visual feature extraction, and uses this as part of a visually derived Wiener filtering system to enhance noisy audio speech signals. The Wiener filter uses Gaussian Mixture Regression (GMM-GMR) [42] to provide an estimate of a noiseless speech signal, trained offline with clean audio speech from a number of speakers, based on extracted visual information. This initial system is trained using a limited number of speakers, limiting the scope of this work. However, the framework is scalable, with potential for expanding the generality of the system. This initially pre-processed speech is then

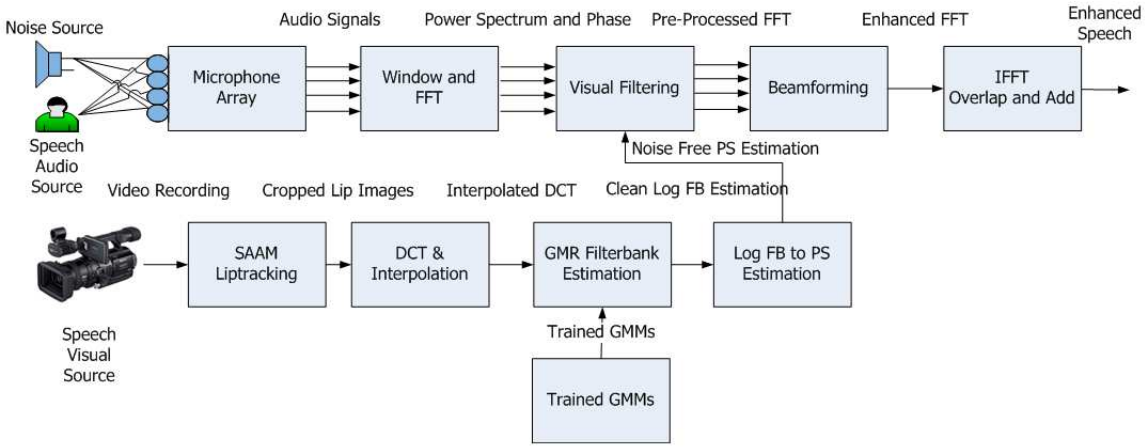


Figure 1: High level diagram of two-stage speech filtering system presented in [1].

filtered with an audio-only TFGSC beamformer. To the knowledge of the authors, this component based two stage framework was not previously demonstrated by any other work in this field. The initial framework presented in [1] is shown in figure 1.

In a previous paper [1], we presented a novel two stage audiovisual speech filtering system that makes use of visually derived pre-processing and audio based beamforming to enhance convolved speech mixtures. This approach extends the idea of two stage audio-only speech enhancement systems to become multimodal with the use of visual information to pre-process noisy speech signals as part of this system. This system is described in full depth in [1], with a brief summary provided in this section.

2.1.1 Reverberant room environment

In order for speech filtering to be performed in an experimental environment, the speech and noise sources have to be mixed. A simple additive mixture does not take into account factors such as the difference in location of source and noise, atmospheric conditions such as temperature and humidity, or reverberation (a natural consequence of broadcasting sound in a room). Here, the noisy speech mixtures used are mixed in a convolved manner. To do this, a simulated room environment is used, with the speech and noise sources transformed with the matching impulse responses. Impulse responses represent the characteristics of a room when presented with a brief audio sample, and these are then applied to the speech and noise signals in the context of their location within the simulated room. This gives them the characteristics of being affected by environmental conditions with regard to microphone input. These sources are then convolved.

2.1.2 Multiple microphone array

In the reverberant room environment, there is an assumption that the signal and noise sources originate from different locations. Within this simulated room, the convolved signals are then mixed and then received by an array of microphones within this room (in a similar manner to directional microphones used in hearing aids). In [1], we specified an array of four microphones, positioned 8 cm apart. This results in four convolved noisy audio signals for processing. These are then Fourier transformed and used for further processing.

2.1.3 Audio feature extraction

The Fourier transformed signals are then used as part of the visually derived filtering process. The signals are transformed again to produce the magnitude spectrum, and subsequently log filterbank values for each microphone input.

2.1.4 Visual Feature Extraction

For each speech sentence, matching visual features are then extracted. This is carried out by using a visual tracking approach [41] to identify the lip region for each frame of a speech sentence. A 2 dimensional Discrete Cosine

Transform was then performed on the extracted lip region to convert the data into a usable format, and this was then upsampled to take account of the difference between sampling rates of the audio and visual signal. This was carried out by duplicating each DCT vector a number of times to match the audio sample rate.

2.1.5 Visually Derived Wiener Filtering

Wiener filtering [8] is a signal processing technique that aims to clean up a noisy signal by comparing a noisy input signal with an estimation of a noiseless signal [43], [3]. One challenging aspect of Wiener filtering is the acquisition of an estimation of the noiseless signal. Unlike some other speech filtering approaches, some knowledge of the original signal is required.In this work, visual information is used to produce an estimate of the noise free signal, which is compared to the transformed noisy audio information to produce a filtered signal. This represents the first stage of filtering in this two-stage approach. The noise free signal is estimated from a trained audiovisual speech model.

2.1.6 Gaussian Mixture Model for Audiovisual Clean Speech Estimation

To estimate the noise free signal, the visual DCT information is used as an input into a Gaussian Mixture Regression (GMR) [42] model, a technique originally designed for training a robot arm. This was trained using a large audiovisual training set comprising of related clean audio filterbank and visual DCT vectors. To then produce an estimated noise free signal, the visual information is used as an input into the trained model, which outputs an estimated noise free signal that can be used for Wiener filtering.

2.1.7 Beamforming

Multiple microphone techniques such as beamforming can improve the quality and intelligibility of speech by exploiting the spatial diversity of speech and noise sources to filter speech. In Abel and Hussain [1], a beamformer proposed orignally by Gannot et al. [6] is used to remove noise from unwanted directions, as the second stage of the filtering process (after visually derived filtering). This involves a fixed beamformer(FBF), a blocking matrix(BM), and a multichannel adaptive noise canceller (ANC). The FBF is an array of weighting filters that suppresses or enhances signals arriving from unwanted directions. The column of the BM can be regarded as a set of spatial filters suppressing any component impinging from the direction of the signal of interest, and these signals are used by the ANC to construct a noise signal to be subtracted from the FBF output. This technique attempts to eliminate stationary noise that passes through the fixed beamformer, yielding an enhanced output signal. An inverse Fourier transform is then performed to produce the enhanced final single output audio signal.

2.2 Evaluation and Conclusions

To evaluate this framework, firstly, the system was tested in environments with very low SNR levels (ranging from -40dB to +10dB). Aircraft noise was added to sentences from the GRID audiovisual speech corpus in a simulated room environment to create convolved noisy mixtures with low SNR levels. It was shown with performance evaluation measures and listening tests that in these environments, this two-stage audiovisual solution produces improved results when compared to unfiltered noise and an audio-only spectral subtraction approach, suggesting that in extremely noisy environments, an element of visual processing can be used effectively as part of a speech enhancement system. Secondly, a noisy speech mixture containing an intermittent clapping and silence noise was presented. It was shown that without the visual pre-processing, the basic audio-only beamformer delivered unusable results. With the addition of the visual pre-processing stage though, the multimodal system was then able to produce usable results.

The system was then thoroughly tested with speech sentences from a corpus that was not used for any part of the training process. It was shown that the results were significantly worse when a different corpus was used for testing, demonstrating that there were some limitations with the system. Significantly, the approach used for audiovisual modelling was found to perform very poorly when tested with a completely novel data, suggesting that this technique is not an optimal approach.

It was established that although the GMM-GMR based approach evaluated in the previous paper can deliver positive results, it does introduce distortion into the overall results, especially at high SNR levels, which suggests that the initial audiovisual model used within this framework for visually derived Wiener filtering can be improved further, and that when presented with completely new visual data, i.e. speakers which the system has not been

trained with, the model used in this paper does not adequately generalise at this time. Although this is a common problem for multimodal speech filtering systems, this is an aspect which will be refined in future work.

A key limitation of the initial system that was identified was that the variation in performance between approaches at different noise levels suggests that there is not a single speech enhancement approach that is guaranteed to deliver optimum results in all conditions. It can be seen that visual information has a big impact in very noisy environments, but hinders results when there is less noise. Furthermore, this initial work did not take account of scenarios such as those where there is no visual information available, such as a situation where the speaker has his head turned or changes in light conditions mean that the lip region of the speaker cannot be seen. This means that audio and visual information need to be used intelligently, depending on availability and suitability of input information. Existing commercially available hearing aids make use of decision rules to decide on the level of speech filtering to apply. As reported by [44], hearing aids exist that can take account of a number of detectors to analyse the input signal in order to classify the noise. Such an idea can also be seen in neuro-fuzzy systems such as by [45] that again seek to classify noise.

3 Fuzzy Logic Based Approach

3.1 Suitability of a Fuzzy Logic Approach

This work proposes to extend the initial multimodal system to make use of audio and visual information in a more autonomous, adaptive and context aware manner using a fuzzy logic controller. This allows for this initial system to be extended in the future with a number of different detectors, as used in other commercial hearing aids ([46]). When a modern programmable hearing aid is provided, patients are expected to undergo fitting sessions, where their hearing aid is programmed to better fit their individual hearing loss and comfort levels. Therefore, any proposed system should contain accessible parameters that can be tweaked and tailored in order to adapt to the hearing ability and preferences of the user.

Several approaches were considered for use as part of this system, such as making use of ANNs, GMMs, HMMs, or a hybrid of these approaches, such as neuro-fuzzy approaches, which use fuzzy inference inputs into a neural network ([45, 47]). Fuzzy logic is an approach that allows for uncertainty to be represented, therefore it is context aware, in that it is capable of responding to different changes in the environment, based on inputs into the system. It is also adaptive, in that it can respond to these inputs, so in the system presented here, the different inputs provide information about the environmental context (such as the level of noise), the fuzzy-system makes a decision regarding the suitable processing choice, depending on this input. It is also is based on expert knowledge; this means that there are a number of rules that can be programmed and tweaked. The preliminary system represented here makes use of very basic detectors, and could theoretically be represented using a different approach, such as with HMMs. However, it would arguably be more difficult to extend, train and implement a more sophisticated version of a HMM based system in future, whereas a fuzzy logic system ([48]) is easier to refine and extend, due to its use of expert knowledge and the clearly defined rule base. The initial two-stage system presented in [1] is extended with the addition of a fuzzy logic controller and a number of fuzzy inputs.

3.2 Fuzzy Based Multimodal Speech Enhancement Framework

3.2.1 Overall Design Framework of Fuzzy System

To integrate the fuzzy logic controller into the multimodal framework described in section 2, the initial system shown in figure 1 is extended further by the integration of a fuzzy logic controller and the subsequent adjustment of the speech filtering options. The same Wiener filtering and beamforming processing options are used. Visual tracking and feature extraction is handled in much the same manner, as is the audio feature extraction process. The only addition is to replace the manual identification of the initial lip region with a Viola-Jones [49] detector, developed by Kroon [50]. With regard to speech processing, the two processing options, visually derived Wiener filtering and audio-only beamforming remain unchanged. However, the difference is that one or both of these stages may be bypassed on a frame-by-frame basis, depending on the inputs received by the fuzzy logic controller. This redesigned framework is shown in figure 2.

The diagram in figure 2 shows the high level extended system diagram with the alternative speech processing options. Depending on the inputs to the fuzzy logic controller, the type of processing performed on the input signal may vary from frame-to-frame. So for example, if it is detected that there is very little audio activity in a particular frame, then it may be decided to leave that frame unfiltered. Alternatively, if a moderate amount of audio energy

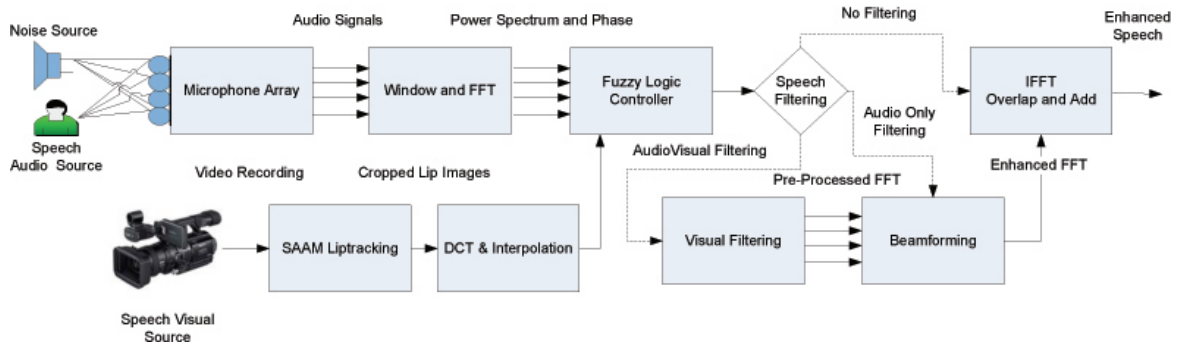


Figure 2: System diagram of proposed fuzzy logic based two-stage multimodal speech enhancement system. This is an extension of figure 1, with the addition of a fuzzy logic controller to receive inputs and decide suitable processing options on a frame-by-frame basis.

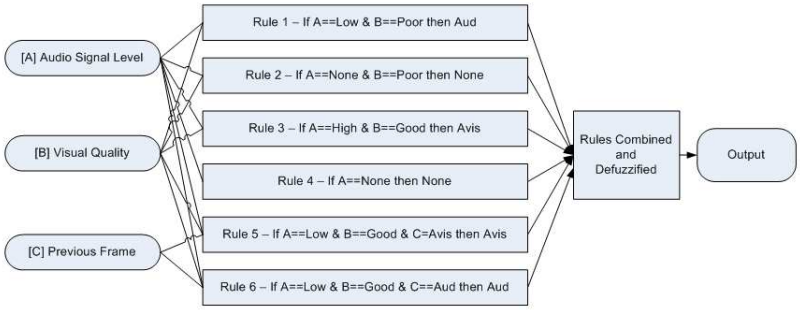


Figure 3: Diagram of fuzzy logic components, showing the three chosen fuzzy inputs and the list of rules to be applied.

is detected, then it may be decided that audio-only beamforming is the most appropriate processing method. If however, a lot of audio activity is detected in a particular frame and the visual information is considered to be of good quality, then the full two-stage process may be used.

The decision as to which option is to be used is taken with the aid of a number of detectors applied to the input signal. Audio-only hearing aids make use of a wide range of proprietary detectors such as level, wind and modulation detectors. In this work, three detectors are used. An audio level detector, a visual quality detector, and a feedback input of the processing decision made in the previous frame. Fuzzy logic rules are then used to determine the most suitable processing method, and each individual frame is processed individually.

3.3 Fuzzy Logic Based Framework Inputs

The fuzzy logic controller builds a relationship between system inputs and the rules used to define the processing selection. In order to accomplish this, it takes a number of input variables and applies these to fuzzy logic rules. Each input variable must be decomposed into a set of regions (or fuzzy sets), consisting of a number of membership functions. The composition of these membership functions can vary in size and shape, based on the preference of the designer ([51]), trapezoid membership functions were used for all inputs in order to ensure consistency. The fuzzy-system diagram is shown in figure 3, and there are three inputs to consider, audio level, visual quality, and previous frame processing decision.

3.3.1 Visual Quality Fuzzy Input Variable

The first input variable is the visual quality. This measures the level of detail found in each cropped ROI. As the system is audiovisual, visual information is a key component of the processing. However, this information can be of varying quality. There are occasions when the entire lip region is visible, but there are also occasions when the lip-tracker returns an incorrect result due to scenarios such as the speaker turning their head. There are also occasions when the lip region may be blurred due to movement, or only a partial ROI is returned. In real world

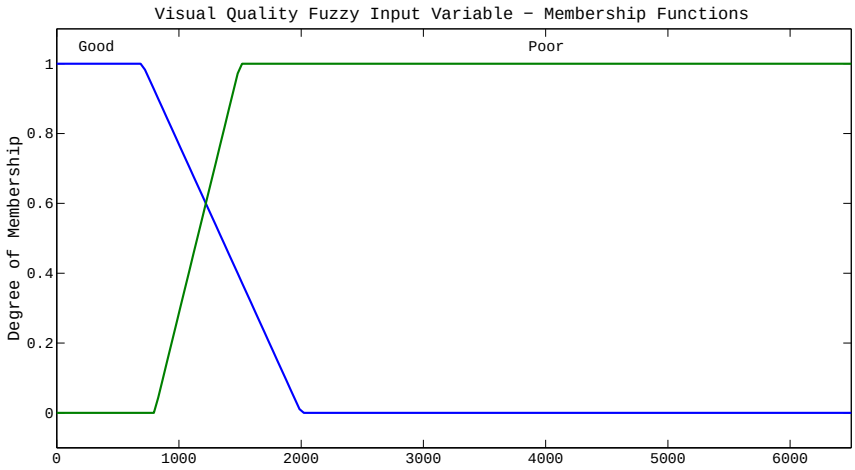


Figure 4: Switching logic input parameter: visual detail level. Depending on the level of visual detail, the estimated parameter can be considered to be 'Good' or 'Poor' to varying extents.

environments, there are many more examples of poor visual data to take account of than found in conventional audiovisual speech databases [52], [53].

As there were many different potential speakers, an approach with as much flexibility as possible was required. One potential approach was to make use of a machine learning technique such as a HMM to create a model to evaluate the ROI and return a score to use as a fuzzy input variable. However, it was felt that this was not required for the initial implementation presented here. Instead, a simpler approach was devised that made use of the input DCT vector. A custom corpus was recorded using real data from a variety of volunteers, as will be discussed in section 4, and a number of trial videos were evaluated to calculate the most suitable value, with various variables investigated, such as the DCT input vector, and the tracker parameters of the actual cropped images. It was established that the fourth DCT coefficient was consistently a better representation of the accuracy of the cropped DCT than any other single factor, and so this was used to create a mean value. As the DCT transform represents pixel intensity, it was calculated that while the value of this would vary from image to image, the fourth coefficient value would remain relatively consistent. Therefore, for each frame, the absolute value (converting negative values to positive) of the fourth DCT coefficient was calculated. This was then compared to a moving average of up to the 10 previous frames that were considered to also be of good quality, and the difference between this moving average and the coefficient represented the visual input variable.

To create this moving average, one assumption was made, that the first value of each sentence was successfully identified with a Viola-Jones detector ([49]). This first value was used as the initial moving average mean value. For the second frame onwards, the new value was compared to the mean of the moving average. If the new value was considered to be within a threshold (preliminary trials identified an appropriate threshold to be 2000), then this value was considered to be suitable, and so was added to the moving average. To take account of variations in speech from frame-to-frame, only a maximum of the 10 most recent values were considered as part of the moving average. This moving average threshold aims to minimise incidences of incorrect results being added to the moving average. The trapezoidal membership functions are shown in figure 4.

Figure 4 shows that there are two membership functions, 'Good' and 'Poor'. The lower the input value, the closer to the mean and therefore the better the frame of visual data was considered to be. It was considered that a visual quality value of less than 800 was definitely an example of a good frame of visual information. Between 800 and 2000, then it could be sometimes considered a partial member of the good set in that there was some ambiguity depending on the speaker, and also there were examples of partial frames (where only part of the ROI was accurate), justifying the decision to use fuzzy logic.

3.3.2 Audio Power Fuzzy Input Variable

The second input variable is the audio power level. This considers the level of acoustic activity in an individual frame of speech. This variable does not consider the problem of voice activity detection, and so does not attempt to

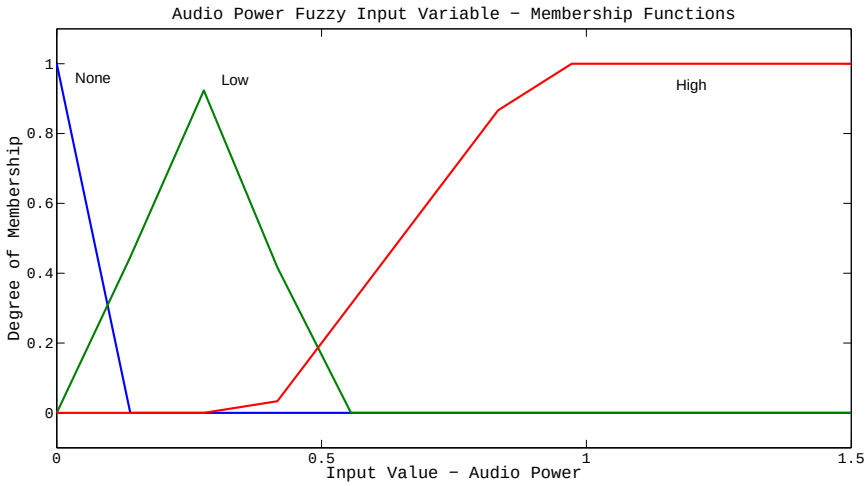


Figure 5: Switching logic input parameter: audio frame power, showing only membership functions for values ranging from 0 to 1.5. Depending on the level of audio power, the estimated parameter can be considered to be 'None', 'Low', or 'High'.

distinguish between speech and noise. It is possible to devise an audiovisual VAD ([43]), and this could represent future potential development as an additional input detector, but it was felt that the most important factor with regard to the proof of concept system was identifying the level of the audio input as in a real environment the level of noise does not remain consistent, and can change from frame-to-frame. In terms of the various conventional hearing-aid input detectors, this input variable functions in a similar manner to a level detector ([46]).

To calculate the audio power in each input speech frame, the frame is first converted back to the time domain, and the mean of the absolute values of the frame is then found. This represents the level of the audio power. The fuzzy set that the audio power input variable belongs to is then calculated based on this input, as shown in figure 5. To take account of extremely noisy input variables, due to the extremely low SNR that the system is tested with, the largest trapezoidal membership function, has a maximum value of 25. Figure 5 shows only the fuzzy membership functions for values less than 1.5, with all values above this considered to belong to the 'High' function.

Figure 5 shows that if the level is recorded as being very low (less than 0.015), it is considered to belong to the 'None' membership function. However, as the level detector is very sensitive, it can be seen that any positive level (ranging from 0.009 to 0.5) is also part of the 'Low' fuzzy-set to an extent. Finally, any values greater than 0.4 were considered to be a member of the 'High' set to an extent, and values greater than 0.9 were considered to fully belong to the 'High' set. These values were set by using trial data.

3.3.3 Previous Frame Fuzzy Input Variable

The third input is a feedback variable that uses the fuzzy controller output from the previous frame. The three trapezoidal membership functions can be seen in figure 6, which is valid for the representation of both the controller output and the third input. The reason for this third input is to act as a smoothing function in marginal cases. For example, the audio and visual inputs may produce input variables that lie near the thresholds between two possible processing options. Small changes in subsequent frames may produce a radically different processing decision from frame-to-frame. As a consequence, the output sound quality may be of poor listening comfort (as is sometimes found in conventional hearing aids when the engage/adaption/attack configuration is set poorly, resulting in a 'choppy' sound, as discussed by [46]).

The use of the previous frame output is designed to limit this. This performs the role of engage/adaption/attack configuration in this preliminary system, as it introduces what is effectively a small delay into processing changes. The use of a mean of several frames as part of an input variable was also considered, and the results of an evaluation of using a different number of frames as part of a mean is presented in section 5. It was concluded from this evaluation that there was no noticeable improvement when using a mean of 3, 5, or 10 previous frames. Therefore, it was considered suitable to use the single previous output value as an input variable. There are

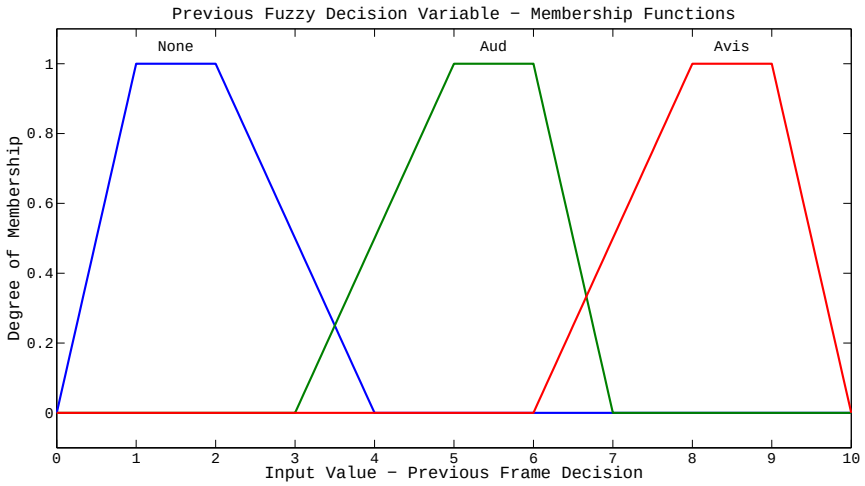


Figure 6: Switching logic input parameter: previous frame output. This input variable considers the processing method chosen in the previous frame. Therefore, this input fuzzy set diagram matches the output choice.

three membership functions, with each one corresponding to a processing decision 'None' (meaning to leave the frame unprocessed), 'Aud' (meaning to use audio-only beamforming), and 'Avis', meaning to use the audiovisual approach. These match the output decision fuzzy sets.

3.4 Fuzzy Logic Based Switching Supervisor

In this framework, the fuzzy logic controller is used to determine the most suitable speech processing method to apply to an individual frame of speech, based on the fuzzy input variables defined in the previous section. The input variables are the audio level (audSigPow), visual quality (visQuality), and the previous frame controller output (prevFrame). An input variable may simultaneously belong to more than one fuzzy set to varying extents.

The processing output options are no processing (a), audio-only processing (b), or two-stage audiovisual processing (c). The complete set of rules used in this system is listed as follows:

- Rule 1: IF audioSigPow IS low AND visQuality IS poor THEN process is b
- Rule 2: IF audioSigPow IS none AND visQuality IS poor THEN process is a
- Rule 3: IF audioSigPow IS high AND visQuality IS good THEN process is c
- Rule 4: IF audioSigPow IS none THEN process is a
- Rule 5: IF audioSigPow IS low AND visQuality IS Good AND prevFrame IS avis THEN process is c
- Rule 6: IF audioSigPow IS low AND visQuality IS Good AND prevFrame IS aud THEN process is b

Rule 1 activates audio-only processing if the audio input variable belongs to the 'Low' fuzzy set and the visual quality is defined as being 'Poor'. Rules 2 and 4 ensure that the frame is left unfiltered if the audio level is found to be so low that the audio level is defined as being 'None'. Rule 3 activates audiovisual processing if there is a sufficient level of noise, and if visual information of an adequate quality is available. Rules 5 and 6 are designed to take effect in scenarios where the potential choice of processing algorithm is ambiguous. If the audio level is defined as 'Low', but 'Good' quality visual information is available, then the previous frame input is also considered. Rule 5 activates audiovisual processing if the previous frame output was also audiovisual, and rule 6 activates audio-only processing if the previous frame decision was audio-only. This is intended to ensure continuity between frames and prevent rapid frame-by-frame changes that act as an irritant to listeners.

4 Audiovisual Corpus

To demonstrate the performance of the fuzzy logic based system, it was considered a requirement to use challenging real world speech data. For this, it was considered necessary to record novel data, the corpora used in previous work by the author (such as VidTimit [52] and GRID [53]) were not considered to be entirely suitable, due to limitations in content and variation of quality. To provide a diverse range of audiovisual speech data, and to provide challenging data that the pre-existing corpora used in previous work (GRID and VidTIMIT) fail to supply, volunteers were asked to perform two tasks. Firstly, a reading task, where they read either a short story or a news article. For this task, they were recorded reading for a minute in a quiet environment.

The second scenario was a conversational task, where volunteers were encouraged to speak in a more natural manner. Volunteers were recorded in pairs at a table facing each other, with one speaker recorded at a time for one minute. By this it is meant that while the speakers were facing each other and making conversation, the camera was only pointed at one speaker. This allowed more natural and relaxed speech, and the volunteers were also told that they were allowed to move freely and did not have to look directly into the camera at all times. This resulted in more noisy visual data such as head turning, speakers placing their hands over their mouths, and blurring in individual frames due to motion. As this was a conversation rather than continuous speech from a single recorded speaker, there were occasional silences, or speech from the other participant in the conversation. This provided challenging data which the system has not been trained with.

To record volunteers carrying out the tasks described above, a single camera was used with an integrated microphone. Due to equipment limitations, the visual data was recorded at 15 fps at a resolution of 640 x 480. For each speaker, there were two minutes of initial raw data available. The final corpus contained data from eight speakers, four male, four female. Six of the eight speakers spoke English (five with a Scottish accent and one English), and two were recorded speaking Bulgarian. For each speaker, two minutes of raw data were theoretically available, one minute of conversation, and of reading. Some example frames of the recorded volunteers are shown in figure 7.

However, there were some issues with the recording process. Firstly, the video camera had automatic brightness adjustment enabled, and so a small number of frames were considerably darker due to occasional automatic readjustment. An example of this can be seen in the lower image in figure 8. There were also a number of glitches in the recording that were discovered afterwards during the review of the data. An example of this can be seen in the top image in figure 8. In this image, the camera has not recorded the head of the speaker in a single frame, although in subsequent and preceding frames, the head is not missing. One other issue was that the recording did not function correctly for one speaker, with some synchronisation issues between audio and visual data. For this reason, there is limited data available from one pair of volunteers.

As part of the requirement for the visual data to be challenging, speakers were expected to move naturally. This led to variable quality visual data, with speakers covering their mouth and turning their head, meaning that lip information is not available, and the ROI therefore cannot be correctly identified. There is also blurring present in this image due to movement. This will be resolved in future work by using a higher quality camera.

The data was divided into 20 second clips because of processing and testing requirements. This sentence length was felt to be long enough to test the operation of the fuzzy-system, while still being short enough to process relatively efficiently. A number of these 20 second clips were then chosen for use as part of the testing process. These were chosen to represent a mixture of different conditions and data quality. The resulting visual data was of variable quality, containing considerably different speech sentences and speakers from those that the system had been previously trained with with examples of turning and movement, as well as varying audio quality due to noise.

5 Experimental Results

5.1 Visual Quality Fuzzy Indicator

5.1.1 Problem Description

There was an assumption made that the initial image frame was accurately detected, and subsequent frames were calculated in terms of the difference from the mean of the absolute value of the fourth DCT coefficient. To take account of natural movement over time, a moving average of the previous 10 frames was used, with only frames that were considered to be within a set threshold added to the moving average. This value was then used as the

Figure 7: Speakers from recorded corpus, using sample frames taken from videos.

Figure 8: Examples of poor quality visual data due to issues with recording. The top image shows an example of a glitch during recording, resulting in the face region being removed. The bottom image shows a situation where light conditions have changed, resulting in a temporarily darker image.

visual fuzzy input value. The assumption made was that if the absolute value of the fourth coefficient was similar to the mean, then the lip image was likely to be very similar, and therefore a good quality image.

For testing, 20 sentences from the corpus were used for evaluation. To ensure that a range of different visual challenges was represented, 10 reading examples, and 10 conversation sentences were used, from a number of different speakers. This ensured that challenging data was used and provided a rigorous test of this fuzzy input variable. For each sentence, a manual review of each cropped lip image was performed. This involved inspecting each frame and assigning it a value. A frame that was considered to be of good quality (in that it showed the whole lip-region) was given a score of 1. An image that was considered to be of lower quality (either showing only part of the lip-region or the wrong region) was given a score of 2. Finally, an extremely poor result (one where no ROI at all was identified) was given a score of 3. This was then compared to the fuzzy input variable.

As this variable can vary in value between 0 and 6000+, with a lower value indicating less difference from the mean, based on preliminary trials, a value of less than 1000 was given a score of 1 (some examples of this are shown in figure 9), a value between 1000 and 4500 was assigned a score of 2 (as shown by the examples in figure 10), and anything greater than 4500 was given a score of 3, representing examples where no ROI was identified, as shown in figure 11. This allowed the visual input variable output to be mapped to the manual estimation. For each sentence, to ensure consistency, the interpolated number of frames was used for comparison, and the fuzzy score was compared to the manually estimated value. The difference between the estimation score and the actual score was then calculated.

5.1.2 Summary of Results

Firstly, when taking all 20 sentences into account (whether recorded in a quiet or noisy environment, or as part of a reading or conversation task), after interpolation there were a total of 39975 frames of data. Of these, 92.15% produced a correct result (one where the fuzzy and manual scores matched), and 7.85% produced what was considered to be an incorrect result, as shown in table 1. Taking into account that 10 of the 20 sentences consisted of active conversation, this was a considered to be a good overall result.

To analyse the results in more detail, a comparison of the number of frames assigned each score is shown in table 2. This table shows the number and percentage of frames assigned each score both manually and using the

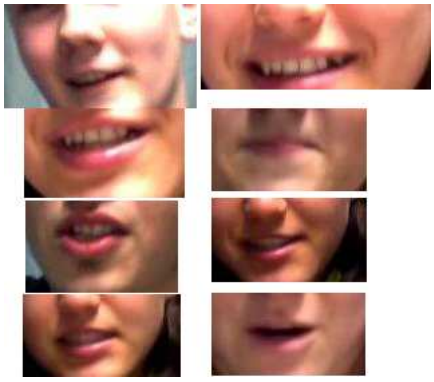


Figure 9: Examples of lip images regarded to be successfully detected. It can be seen that the images are of varying dimensionality, and also include different levels of additional facial detail depending on the results of the Viola-Jones lip detector.

Figure 10: Examples of lip images regarded to be unsuccessfully detected. It can be seen that the images are of varying dimensionality, with issues such as identifying the wrong area of an image as the ROI, tracking only part of the lip-region, or poor quality information due to blurring and head motion.

Figure 11: Examples of lip images where no ROI was identified and cropping was not successful. It can be seen that this is due to the speaker turning their head or obscuring their face.

Table 1: Overall performance of visual quality fuzzy input variable compared to manual scoring, considering each frame of all 20 speech sentences.

	Number of Frames	Percentage
Correct	36836	92.15%
Incorrect	3139	07.85%
Total	39975	100%

Table 2: Comparison of assigned values for overall 20 sentence dataset, showing difference in estimated value for manual inspection and fuzzy logic variable.

Method	Assigned Value	No. frames	Perc. of total
Manual	1	36334	90.89%
Manual	2	3168	7.93%
Manual	3	473	1.18%
Fuzzy	1	37779	94.51%
Fuzzy	2	1749	4.38%
Fuzzy	3	447	1.12%

Table 3: Error between estimated visual fuzzy input and manual value for each frame of all 20 speech sentences.

Est. Val.	Manual Est.	Fuzzy Est.	Diff.	Diff. Perc.
1	36334	37779	1445	3.977%
2	3168	1749	1419	44.79%
3	473	447	26	5.497%

fuzzy input variable. When observing the manually categorised frame scores, 90.89% were considered to be good frames, 7.93% were considered to be incorrectly assigned frames, and 1.18% of frames were considered to have identified no correct ROI. In comparison, the estimated fuzzy scores were slightly different. 94.51% of frames were considered to be good frames, 4.38% were estimated to be incorrect, and 1.12% were considered to have identified no correct ROI.

Table 2 shows that the number of frames considered to have no ROI were very similar, with the greatest difference being that a higher number of fuzzy scores were estimated to be suitable than for a manual inspection. This is unsurprising due to the variation between speakers, sentences, cropped ROI dimensionality, and represents a justification for the use of a fuzzy logic variable. The difference in estimated values between the manual and the fuzzy approach is shown in table 3. This table shows that 3.98% of frames were incorrectly categorised as being good values (i.e. the difference between the ground truth and automatic values), 5.5% were incorrectly estimated to identify no ROI, and 44.8% were estimated to incorrectly be estimated as having a value of 2 (i.e. an incorrect/blurry/partial region). This was unsurprising as the difference between good and poor values could sometimes be very small, and indicates that the detector may have limitations with regard to precise identification of correct but partial regions.

To analyse the incorrect classification results shown in table 3 in more depth, individual sentences were examined in order to identify if differences between the fuzzy estimation and the manual evaluation were evenly split, or were concentrated in specific sentences. Each of the 10 sentences was evaluated to compare the difference in results. Considering the reading task first, the results are shown in table 4.

Table 4 shows that as expected, the percentage of matching fuzzy and ground truth values predicted is above 94% for reading all cases, with only a very small number of results where the fuzzy estimation does not match

Table 4: Comparison of assigned values for 10 sentence reading dataset, showing difference in estimated value for manual inspection and fuzzy logic variable.

Sent.	No. Correct	Perc. Correct	No. Incorrect	Perc. Incorrect
1	1933	96.70%	66	3.30%
2	1992	99.65%	7	0.35%
3	1974	98.75%	25	1.25%
4	1985	99.30%	14	0.70%
5	1880	94.05%	119	5.95%
6	1926	96.59%	68	3.41%
7	1952	97.65%	47	2.35%
8	1915	95.80%	84	4.20%
9	1957	97.90%	42	2.10%
10	1999	100%	0	0%

Table 5: Comparison of assigned values for 10 sentence conversation dataset, showing difference in estimated value for manual inspection and fuzzy logic variable.

Sen.	No. Correct	Perc. Correct	No. Incorrect	Perc. Incorrect
1	1836	91.85%	163	8.15%
2	1432	71.64%	567	28.36%
3	1999	100%	0	0%
4	1947	97.40%	52	2.60%
5	1840	92.05%	159	7.95%
6	1930	96.55%	69	3.45%
7	676	33.82%	1323	66.18%
8	1689	84.49%	310	15.51%
9	1978	98.95%	21	1.05%
10	1996	99.85%	3	0.15%

Figure 12: Examples of lip tracker extracting an incorrect image for a sequence of frames. These frames were consecutive frames from a single sentence and show that while a manual investigation may identify this as a partial result, the fuzzy input may be more nuanced, due to most of the mouth being present.

the manual evaluation. In comparison, table 5 shows the match between the fuzzy estimation and the manual evaluation for the 10 sentences chosen for the conversation task.

Table 5 shows that the variation between individual sentences is much higher, which is to be expected considering the issues the tracker faces with conversational speech. Although 6 of the 10 conversational sentences have a higher correct percentage than 90%, there is particular error concentrated in one sentence, with 66.18% of frames showing a difference between the manual and fuzzy estimation. An inspection of this specific cropped image sequence identified that the reason for this was that while the tracker initially identifies a correct ROI, there is an issue in that due to the specific features of this face, a large number of frames are considered to be partial and only show a percentage of the mouth. While a manual inspection resulted in these being classified as partial results, the majority of the mouth was shown in these frames, as shown in figure 12, and so the difference was relatively small, resulting in the fuzzy value assigning these a score that was within the range of being considered good quality data. This indicates the difficulties with giving a precise score of 1, 2, or 3.

In summary, the visual input fuzzy variable was considered to be very accurate, with the majority of frames being correctly classified. It can be seen that the majority of errors were found when conversation data was used. In particular, one specific sentence in the test-set was shown to have a greater error than any other sentence, and an inspection of the data demonstrated that this could be identified as due to potential ambiguity over the quality of the visual data, thus justifying the use of fuzzy logic rather than crisp sets, and demonstrating that the chosen thresholds are reasonably accurate and lead to correct classification in the majority of cases. There is scope for improvement using a form of machine learning such as a HMM to build a classification model, but it was felt that the technique used to calculate the input variable was shown to be successful.

5.2 Previous Frame Fuzzy Input Variable

5.2.1 Problem Description

As described in section 3.2, one input variable used in the system was the previous frame fuzzy output decision. The aim of this variable was to prevent rapid switching from frame-to-frame and there were very small differences from frame-to-frame, meaning that a small change in environmental conditions may result in rapid changes in processing decision from frame-to-frame. Rapid oscillation between processing options can reduce listener comfort, and should be minimised. It was possible that using a moving average of the previous outputs could be more

Table 6: Number and percentage of frames with a difference in fuzzy output decision greater than or equal to 1, compared to previous frame.

	Prev. Frame		Mean of 3		Mean of 5		Mean of 10	
Sent.	No.	% Diff	No.	% Diff	Diff	% Diff	Diff	% Diff
1	40	2.00%	39	1.95%	40	2.00%	40	2.00%
2	119	5.95%	120	6.00%	120	6.00%	122	6.10%
3	34	1.70%	34	1.70%	34	1.70%	34	1.70%
4	9	0.45%	16	0.80%	17	0.85%	18	0.90%
5	10	0.50%	13	0.65%	14	0.70%	18	0.90%
6	24	1.20%	30	1.50%	30	1.50%	29	1.45%
7	22	1.10%	22	1.10%	22	1.10%	22	1.10%
8	109	5.45%	112	5.60%	110	5.50%	110	5.50%
9	120	6.00%	118	5.90%	118	5.90%	121	6.05%
10	0	0%	0	0%	0	0%	0	0%
11	43	2.15%	68	3.40%	74	3.70%	64	3.20%
12	64	3.20%	77	3.85%	84	4.20%	87	4.35%
13	48	2.40%	48	2.40%	48	2.40%	48	2.40%
14	167	8.35%	169	8.45%	171	8.55%	172	8.60%
15	174	8.70%	174	8.70%	174	8.70%	174	8.70%
16	4	0.20%	4	0.20%	4	0.20%	4	0.20%
17	12	0.60%	16	0.800%	17	0.85%	15	0.75%
18	11	0.55%	11	0.550%	11	0.55%	11	0.55%
19	8	0.40%	8	0.400%	8	0.40%	8	0.40%
20	4	0.20%	4	0.200%	4	0.20%	4	0.20%
21	110	5.50%	108	5.403%	108	5.40%	109	5.45%

effective in reducing switching than using a single value. This section investigates the effect of making use of the single previous output and compares this to using a mean of the previous 3, 5, and 10 previous output decisions.

A small dataset of 3 sentences from the corpus was used for evaluation. Broadband machine noise was added to these sentences using the simulated room environment at varying SNR levels to produce 18 noisy speech sentences with a range of audio and visual fuzzy input variables. In addition to this 3 sentences that did not have noise added to them, but were recorded in a noisy environment were also used, producing a total of 21 sentences.

The 21 sentences were evaluated four times using the fuzzy logic system, using the single previous output decision, the mean of the value for the previous 3 outputs, the mean of the previous 5 outputs, and the mean of the previous 10 outputs as the input variable. The resulting output processing decision from the fuzzy logic system was then compared to the decision from the previous frame to calculate the difference between frames. As the system is fuzzy, it is possible for the output decision to vary very slightly from frame-to-frame, without the difference being large enough to affect the processing decision (i.e. no processing, audio-only, or audiovisual), and so it was felt of more relevance to focus on frames where there was a difference in output decision from the previous frame greater than 1.

5.2.2 Summary of Results

A detailed inspection of fuzzy switching performance will be discussed later in this paper, but we first evaluate whether the difference in output decision between frames is affected by using the previous value alone, or a mean of the previous 3, 5, or 10 outputs. Firstly, table 6 shows the number of frames where a difference is found from the previous frame, showing the total number of frames with a difference and the percentage of the total frames, for the four different previous input variables. As discussed, it was decided to filter the data by only considering values where the difference from the previous frame is greater to or equal plus or minus 1.

Table 6 shows that there is a difference between frames from the previous frame on a relatively low number of occasions, as low as 0%, and as high as 8.7%. The difference between individual sentences is to be expected considering the different noise conditions. It can be seen that the difference between using a single frame and a mean of previous frames is relatively small.

Table 7: Number and percentage of frames with any difference of in fuzzy output decision compared to previous frame, showing results when smoothing rule is enabled and disabled for one frame, mean of 3 frames, mean of five frames, and mean of 10 frames.

	Prev. Frame	
Rule	No. Diff	Perc Diff.
Enabled	1132	2.697%
Disabled	2460	5.856%
	Mean of 3	
Rule	No. Diff	Perc Diff.
Enabled	1191	2.837%
Disabled	2460	5.856%
	Mean of 5	
Rule	No. Diff	Perc Diff.
Enabled	1208	2.878%
Disabled	2460	5.856%
	Mean of 10	
Rule	No. Diff	Perc Diff.
Enabled	1210	2.882%
Disabled	2460	5.856%

The second aspect of this evaluation concerned the impact that this fuzzy input variable had on reducing the oscillation from frame-to-frame. To investigate this, the fuzzy logic system was adjusted to disable the rules concerning the previous input variable, in effect meaning that the system made use of only the audio and visual input variables at all times.

Table 7 shows that when the fuzzy rule pertaining to reduction of oscillation is enabled, increasing the number of previous decisions used as part of the mean input variable results in a very small increase in difference. When only the single previous output decision is used as the input variable, 1132, or 2.7% of the total 41980 frames show a change in decision. Using a mean of the 3 previous decisions results in a change of 2.8%, increasing to 2.9% when a mean of 5 previous decisions, and then finally 2.9% when a mean of the 10 previous decisions is used. Overall, the difference between frames when using an increased number of previous decisions as part of the input mean variable was considered to be so small that it had no particularly noticeable difference. Therefore, it was felt that it was suitable to use only the previous decision as an input variable into the fuzzy logic system.

Regarding the effect of disabling the fuzzy input variable, the results presented in table 7 are of interest for several different reasons. Firstly, when disabled, there is no change at all in output when a different number of previous decisions are part of the mean input variable. This confirms that this input variable has a role in affecting the output decision. With the fuzzy input not used, the percentage of frames with a recorded difference varies from 2.7% to 2.88%. With this input variable not used, 5.86% of frames record a difference in output decision from the previous frame. Therefore, it can be concluded that the use of this input variable successfully limits processing decision variation from frame-to-frame.

5.3 Fuzzy System Audio Performance Evaluation

As the input variables were evaluated individually in the previous section, this section focused on the audio performance of the fuzzy switching system. To do this, the composite measures [54] used in previous work by the authors [1] and others [43] are used to perform a detailed evaluation. The output of using the fuzzy logic processing system was compared to mean values calculated by using a number of other techniques, including spectral subtraction, the two-stage audiovisual approach, audio-only beamforming, and the unfiltered noisy speech. In addition to this, it was felt that it would be suitable to run a number of listening tests to evaluate the subjective quality of the speech. As each speech sentence had a duration of 20 seconds, to prevent listener fatigue, three versions of each sentence were evaluated, audiovisual, audio-only, and the fuzzy logic approach. In addition, the number of 20 second conversation snippets tested was limited to 5. These were then tested with volunteers to produce a suitable Mean Opinion Score (MOS).

However, the focus on this paper is primarily on the performance of the switching system rather than on the expected limited audio performance. Therefore, in addition to the audio output, the fuzzy switching is evaluated

Table 8: Composite objective mean test score table for overall speech quality for speech with washing machine noise added, for audiovisual speech, audio-only beamforming, fuzzy-based processing, audio-only spectral subtraction, and unprocessed speech.

Level	Avis	Beamform	Fuzzy	Spectral	Noisy
-40dB	1.482	3.5078	1.110	2.136	2.557
-30dB	1.672	3.802	1.108	2.341	2.445
-20dB	1.798	3.994	2.054	1.904	2.233
-10dB	1.720	4.063	3.534	1.806	1.818
0dB	1.315	4.089	3.903	2.573	2.485
+10dB	0.665	4.102	3.800	3.117	3.083

Table 9: Composite objective mean test score table for speech score speech quality for speech with washing machine noise added, for audiovisual speech, audio-only beamforming, fuzzy-based processing, audio-only spectral subtraction, and unprocessed speech.

Level	Avis	Beamform	Fuzzy	Spectral	Noisy
-40dB	1.649	4.415	1.373	2.121	2.561
-30dB	1.786	4.642	1.401	2.292	2.490
-20dB	1.874	4.790	2.391	2.059	2.394
-10dB	1.729	4.846	4.226	2.199	2.253
0dB	1.128	4.870	4.676	3.021	3.000
+10dB	0.115	4.882	4.536	3.625	3.682

in section 5.4.

5.3.1 Objective Testing With Broadband Noise

Each 20 second snippet of either conversation or reading had broadband machine noise added at different SNR levels, ranging from -40dB to +10dB. Each mixture of speech and noise was then evaluated with the composite objective measures developed by [54]. Five versions of each sentence were compared, firstly, the audiovisual two-stage system presented in [1]. As this approach was shown to perform poorly with completely novel speakers, then it was expected that this approach would perform poorly when tested with the newly recorded corpus. In addition to this, the results of performing audio-only beamforming are also presented. As the simulated room is designed to demonstrate the performance of the beamformer, it is expected that the results of using this technique will be extremely good in suitable environments. The noisy unfiltered sentence is also compared, along with conventional spectral subtraction [55]. These are compared to the results of using the fuzzy-based system. The means of the composite overall, speech distortion, and background distortion at different SNR levels are provided in tables 8, 9, and 10 respectively.

Considering the overall score first, the audio-only beamformer produced the best overall score, which was expected. The unfiltered and spectral subtraction scores are very similar, which matches expectations based on the results presented in previous work. It can also be seen that the audiovisual approach is the worst performing

Table 10: Composite objective mean test score table for noisy speech quality for speech with washing machine noise added, for audiovisual speech, audio-only beamforming, fuzzy-based processing, audio-only spectral subtraction, and unprocessed speech.

Level	Avis	Beamform	Fuzzy	Spectral	Noisy
-40dB	1.842	2.770	1.630	1.995	1.957
-30dB	1.910	3.001	1.591	2.116	1.889
-20dB	1.917	3.331	2.101	1.847	1.753
-10dB	1.835	3.750	3.285	1.774	1.476
0dB	1.620	3.799	3.592	2.224	1.898
+10dB	1.359	3.816	3.429	2.519	2.341

Table 11: Selected results of Bonferroni Multiple Comparison, showing P-Value results for difference between Audiovisual Filtering and Fuzzy Processed Speech with washing machine noise added for overall composite scores.

Level	Diff. of Means	SE of Diff.	T-Value	Adjusted P-Value
-40dB	-0.372	0.144	-2.589	1.000
-30dB	-0.564	0.144	-3.926	0.053
-20dB	0.256	0.144	1.782	1.000
-10dB	1.814	0.144	12.639	0.000
0dB	2.588	0.144	18.030	0.000
+10dB	3.135	0.144	21.84	0.000

Table 12: Selected results of Bonferroni Multiple Comparison, showing P-Value results for difference between Audio-only beamforming and Fuzzy Processed Speech with washing machine noise added for overall composite scores.

Level	Diff. of Means	SE of Diff.	T-Value	Adjusted P-Value
-40dB	-2.398	0.1435	-16.70	0.0000
-30dB	-2.694	0.1435	-10.18	0.0000
-20dB	-1.940	0.1435	-13.52	0.0000
-10dB	-0.529	0.1435	-3.68	0.1317
0dB	-0.187	0.1435	-1.31	1.0000
+10dB	-0.302	0.1435	-2.104	1.0000

method, which again matches expectations due to the limitations of the audiovisual model. The performance of the fuzzy-based system is of interest. The results of Bonferroni multiple comparison for the difference between the audiovisual and fuzzy logic approach, and the audio-only and fuzzy approach are given in tables 11 and 12. The difference of means in table 11 shows that at a very low SNR (at SNR levels of -40dB, -30dB, -20dB), the fuzzy logic approach is the worst performing approach. However, although it is the worst performing approach the difference between the audiovisual and fuzzy approaches was not statistically significant ($p > 0.05$). This suggests that as the noise level is extremely high, the fuzzy logic system makes use of the audiovisual method, which explains the lack of difference.

At higher SNR levels, when there is less noise, the fuzzy-system makes more use of the audio-only approach, and so as shown by the comparison of means in table 12, the difference between the fuzzy-system at these higher SNR levels is not statistically significant ($p > 0.05$). However, the scores do not match exactly. This is because the fuzzy-system does not make use of the same approach in all frames, as it switches in response to precise changes in input variables.

5.3.2 Subjective Testing with Broadband Noise

This section reports the results of listening tests performed on this dataset. 10 volunteers took part in listening tests in a quiet room, using noise cancelling headphones. All of the volunteers spoke English as a first language, and none reported any abnormalities with their hearing. There were 6 male subjects and 4 female subjects, with an age range between 21 and 37. Listeners were played sentences randomly from the test-set, and were asked to score each between 0 and 5. This section discusses overall speech quality Mean Opinion Scores (MOS) results. As there were concerns over listener fatigue due to the potential duration of listening tests using the entire dataset (due to the length of each sentence), a smaller subset of the test-set was used. 5 sentences were selected (again, a mix of reading and conversation tasks), from different speakers, and broadband noise was added at 6 different SNR levels. 3 processing methods were used, the audiovisual approach, the audio-only approach, and the fuzzy-based system. The overall MOS results are shown in figure 13.

Figure 13 shows that the scores for subjective listening tests look very similar to the results presented in section 5.3.1. The audiovisual approach is consistently identified to have the worst output scores, and the audio-only technique returns the best results. The fuzzy-based approach performs poorly at a very low SNR, but has an improved output at a higher SNR. A more detailed analysis, using Bonferroni multiple comparison is shown in the interaction plots in figure 14, and the difference of means is given in tables 13, and 14.

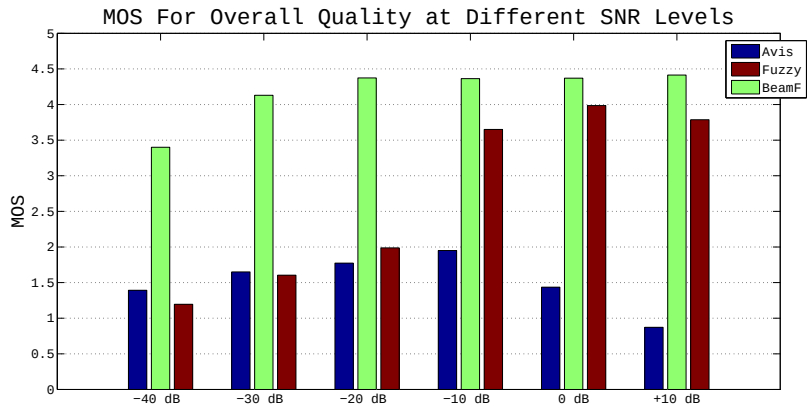


Figure 13: Mean Opinion Score for overall speech quality for speech with washing machine noise added, for audiovisual speech, audio-only beamforming, and fuzzy-based processing.

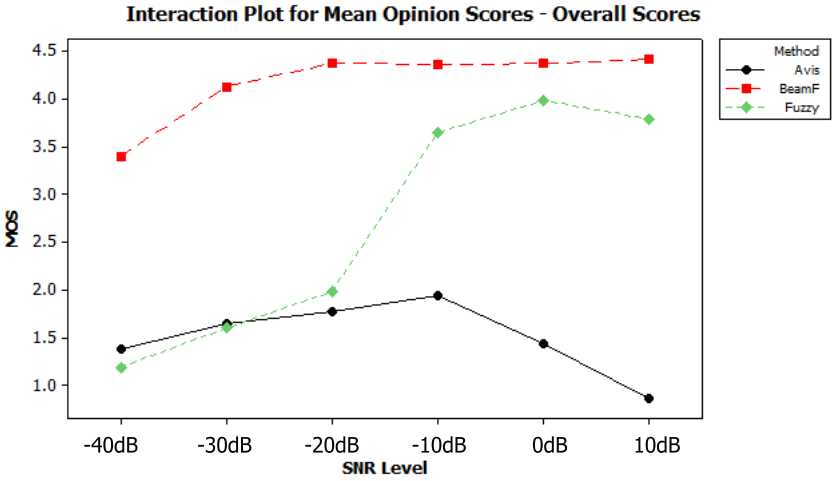


Figure 14: Interaction plot for overall MOS at varying SNR levels, showing audiovisual speech (black and circle markers), audio-only beamforming (red with square markers), and fuzzy-based system (green with diamond markers).

Table 13: Selected results of Bonferroni Multiple Comparison, showing P-Value results for difference between Audio-only beamforming and Fuzzy Processed Speech for overall subjective scores.

Level	Diff. of Means	SE of Diff.	T-Value	Adjusted P-Value
-40dB	-2.204	0.180	-12.23	0.000
-30dB	-2.526	0.180	-14.02	0.000
-20dB	-2.386	0.180	-13.24	0.000
-10dB	-0.714	0.180	-3.96	0.012
0dB	-0.384	0.180	-2.13	1.000
+10dB	-0.627	0.180	-3.479	0.081

Table 14: Selected results of Bonferroni Multiple Comparison, showing P-Value results for difference between Audiovisual Filtering and Fuzzy Processed Speech for overall subjective scores.

Level	Diff. of Means	SE of Diff.	T-Value	Adjusted P-Value
-40dB	-0.196	0.180	-1.088	1.000
-30dB	-0.046	0.180	-0.255	1.000
-20dB	0.214	0.180	1.188	1.000
-10dB	1.700	0.180	9.434	0.000
0dB	2.550	0.180	14.151	0.000
+10dB	2.915	0.180	16.18	0.000

It can be seen that the trend of results is very similar to the objective scores. At a lower SNR, the audiovisual and fuzzy-based scores are very similar, with no significant difference. This signifies that there was a far greater preference by listeners for the sentences processed with audio-only beamforming. When the SNR is increased, the fuzzy-based approach produced an improved score, with a similar output to the audio-only approach, with the results of Bonferroni multiple comparison showing that at SNR levels of -10dB, 0dB, and +10dB, the overall scores were not significantly different ($p > 0.05$). This indicates that listeners found these sentences to be very similar in terms of overall results.

These results also confirm that the fuzzy-based system performs as expected. At lower SNR levels -40dB to -20dB), the fuzzy MOS is very similar to the audiovisual MOS, with small but not significant differences, as shown by the results of a comparison of means. At SNR levels of -10dB and 0dB, the audio-only and fuzzy-based results are very similar, suggesting that audio-only processing is used more often. However, the results also show that similarly to the objective results in the previous section, the audiovisual MOS is the worst performing technique, and the audio-only approach far outperforms this method. However, these results should be interpreted with a degree of caution.

5.3.3 Objective Testing with Inconsistent Transient Noise

Objective and subjective testing identified that the audio-only beamforming approach produced the strongest results. As expected, the audiovisual approach performed poorly when tested with novel data that it had not been trained with, and the fuzzy logic approach produced output that resulted in a poorer score than the audio-only approach due to the fuzzy switching system. However, there should be a degree of caution in interpreting these results. Firstly, although the output audio quality for the fuzzy logic processing approach produces lower objective and subjective scores, this is due to limitations with the audiovisual processing approach, rather than with the fuzzy switching. Secondly, although the audio-only results have been identified as producing the strongest results, this is in a scenario with broadband noise from a fixed source, where a beamformer would be expected to perform well.

In this section, a different noise is used, one with silence and clapping, that represents a greater challenge. A mixture of clapping and silence is used as the noise source, and the 10 speech sentences described above are mixed with the noise source at a range of SNR levels, from -40dB to +10dB. These noisy sentences are then processed using the techniques also used in section 5.3.1, and evaluated using the objective composite measures. The means of the overall scores at different SNR levels are shown in figure 15.

It can be seen that the audio-only beamformer returns the same score at all SNR levels. Listening to the audio output confirmed that the reason this score was so low and so consistent was because no audio signal was returned. The audiovisual score was also poor, but listening to the output confirmed that an audio signal could be heard, hence the higher yet still very low score. The results of Bonferroni multiple comparison, as shown in tables 15 and 16 show that despite the lack of output signal, the difference between the fuzzy output and the audio-only output is only significant at a SNR of -40dB, and 0dB (where $p < 0.05$). The difference between the audiovisual and fuzzy output scores was not significant at any SNR level.

Overall, the results demonstrated that the audio-only beamforming results presented in the previous sections should be interpreted with a degree of caution. The fuzzy logic based results presented in this section are very dependent on the techniques used for processing speech. Although previous sections reported that the audio-only approach produced clearly better results, this was when the noise was one which the beamformer was capable of processing. Likewise, the audiovisual results were shown to be limited due to the system not being trained with data similar to that used for testing. Therefore, although the fuzzy logic system is functioning as expected and is

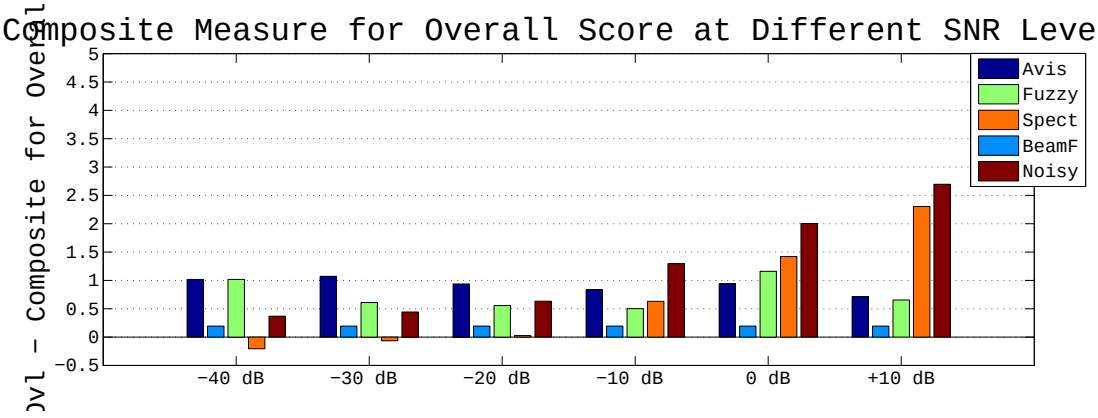


Figure 15: Composite objective mean test scores for overall speech quality for speech with transient clapping noise added, for audiovisual speech, audio-only beamforming, fuzzy-based processing, audio-only spectral subtraction, and unprocessed speech.

Table 15: Selected results of Bonferroni Multiple Comparison, showing P-Value results for difference between Audio-only beamforming and Fuzzy Processed Speech with transient clapping noise added for overall composite scores.

Level	Diff. of Means	SE of Diff.	T-Value	Adjusted P-Value
-40dB	0.824	0.148	5.585	0.000
-30dB	0.416	0.148	2.816	1.000
-20dB	0.363	0.148	2.462	1.000
-10dB	0.307	0.148	2.079	1.000
0dB	0.965	0.148	6.543	0.000
+10dB	0.461	0.148	3.124	0.905

Table 16: Selected results of Bonferroni Multiple Comparison, showing P-Value results for difference between Audiovisual Filtering and Fuzzy Processed Speech with transient clapping noise added for overall composite scores.

Level	Diff. of Means	SE of Diff.	T-Value	Adjusted P-Value
-40dB	0.002	0.148	0.011	1.000
-30dB	-0.463	0.148	-3.138	0.864
-20dB	-0.380	0.148	-2.577	1.000
-10dB	-0.333	0.148	-2.254	1.000
0dB	0.220	0.148	1.490	1.000
+10dB	-0.056	0.148	-0.379	1.000

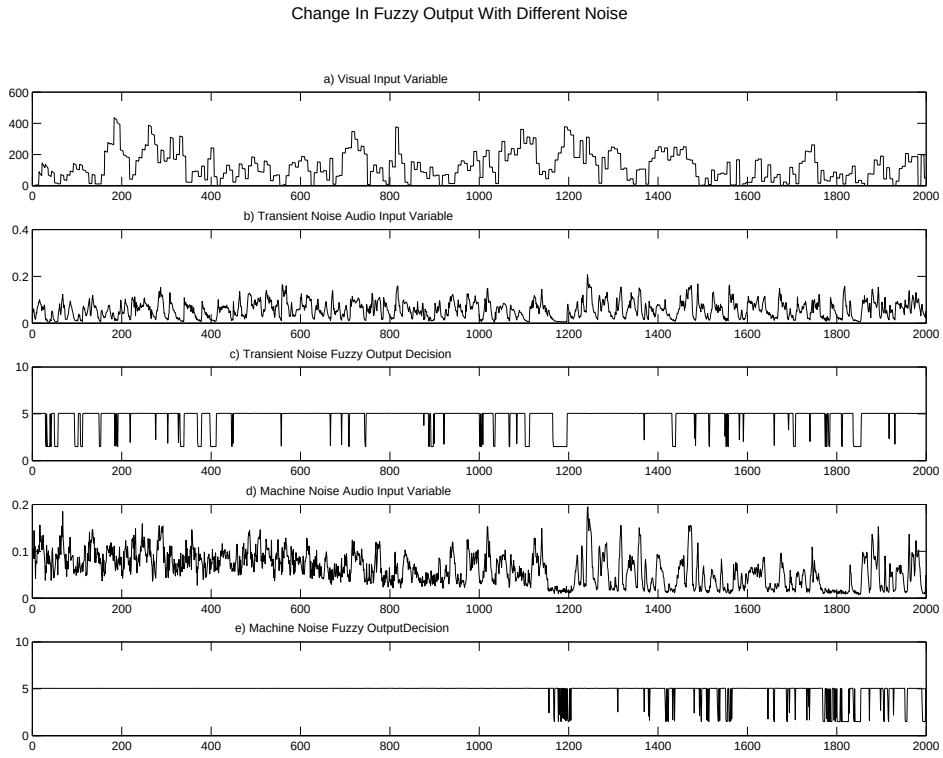


Figure 16: Comparison of fuzzy logic output decision depending on noise type at SNR of 0dB. (a) shows the input visual information. It can be seen that all values are below 600, therefore every frame is considered to be good quality. As the visual information is unchanged, then this is the same for both transient and machine noise speech mixtures. (b) shows the transient mixture fuzzy input variable. (c) shows the associated transient noise mixture output processing decision. (d) shows the machine noise mixture fuzzy input variable. (e) shows the machine noise mixture output processing decision.

switching between techniques, the results are limited by limitations in the specific speech processing techniques, which will be addressed in future work.

5.4 Fuzzy System Switching Performance Evaluation

As discussed previously, it can be seen that the fuzzy logic output varies depending on factors such as the SNR level and the previous output decision value, and the results of subjective and objective tests show that the output mean scores are often similar, but not identical to either the audio-only output scores or the audiovisual scores. However, as a range of sentences (with different associated visual quality fuzzy values), noises, and SNR levels were tested, it was felt suitable to examine the performance of the fuzzy switching approach in detail.

5.4.1 Fuzzy Switching with Varying Noise Type

Firstly, the difference between sentences mixed with the two different noises used in this paper (broadband noise and transient clapping) is examined. To do this, two sentences are compared, with different noise added. The fuzzy output decision from frame-to-frame of a sentence with transient noise is compared to the frame-by-frame output decision of the same sentence, except with the machine noise added at the same SNR. Firstly, noise was added at a SNR of 0dB to the sentence, and the output is shown in figure 16. In order to ensure that good quality visual information was available at all times, an example of a sentence from the reading task was chosen.

Figure 16 shows the difference in the fuzzy output decision, depending on the input noise variable. As the

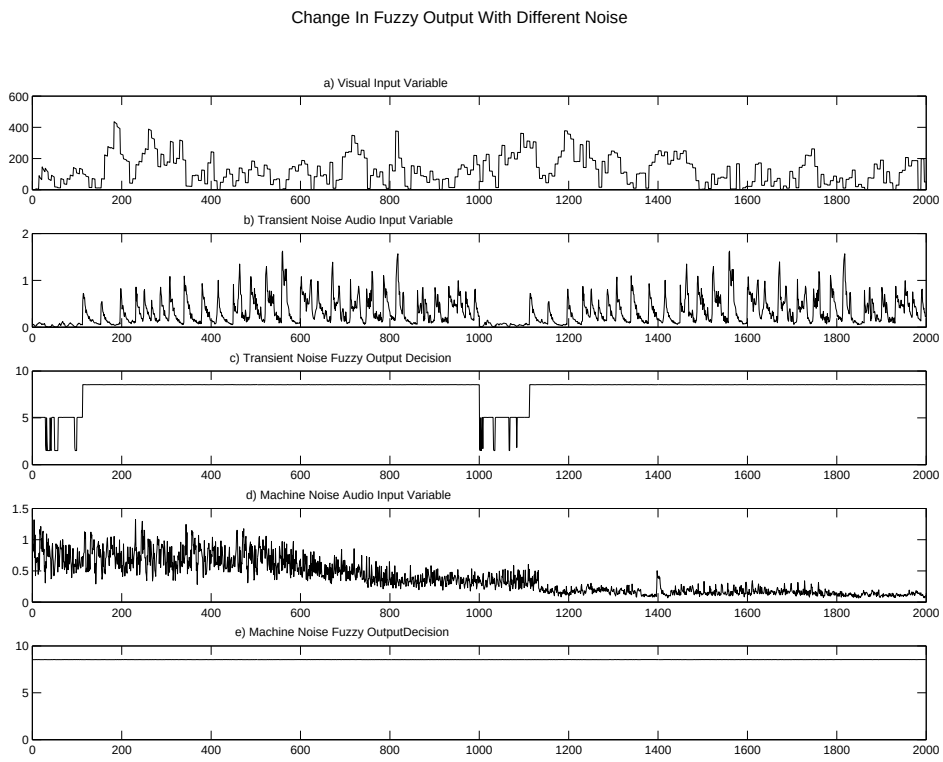


Figure 17: Comparison of fuzzy logic output decision depending on noise type at a SNR of -20dB. (a) shows the input visual information. It can be seen that all values are below 600, therefore every frame is considered to be good quality. As the visual information is unchanged, then this is the same for both transient and machine noise speech mixtures. (b) shows the transient mixture fuzzy input variable. (c) shows the associated transient noise mixture output processing decision. (d) shows the machine noise mixture fuzzy input variable. (e) shows the machine noise mixture output processing decision.

visual information, SNR, and sentence content was the same for both values, the only difference was the noise type. In figure 16, (c) Shows the fuzzy output decision, based on the visual input variable in (a), and the audio input in (b). It can be seen that the noise is of a relatively low level, and so the system alternates between making use of the audio-only (fuzzy value varying around 5) and the unprocessed speech options, which is to be expected when it is considered that this noise consists of handclaps and silences. (e) Shows the fuzzy output decision, based on the inputs in (a), (d). It can be seen that with a different noise, the fuzzy decision is different from (c), as the audio input variable is different. The machine noise is a broadband noise, and so there is more noise present. The broadband noise amplitude gradually decreases over time, and this is reflected in the fuzzy output, which uses the audio-only output decision initially, but as the noise level decreases, the unfiltered output (fuzzy value varying around 1) is chosen on some occasions. This is in line with expectations and shows that the system is performing as expected with different noise types. To confirm this, the same sentence and noises are compared again in figure 17, except with the speech and noise mixed at a SNR of -20dB.

Again, the key information is shown in the fuzzy output decisions in (c) and (e) of figure 17. With the transient noise, it can be seen in (c) that there are two large quiet periods. In these periods, either the unfiltered or audio-only options are chosen, otherwise, the audiovisual output is chosen as expected. In (e), although the noise is gradually decreasing as shown in (d), as the SNR is low the audiovisual output is chosen in all frames.

In summary, it can be seen that the fuzzy output decision varies based purely on the noise type. Figures 16 and 17 show that when the same speech sentence with the same quality of visual information is mixed with noise at the same SNR, with the only difference being the type of noise, the frame-by-frame fuzzy output decision is different. This demonstrates that the fuzzy-based system is capable of adapting to different noise types.

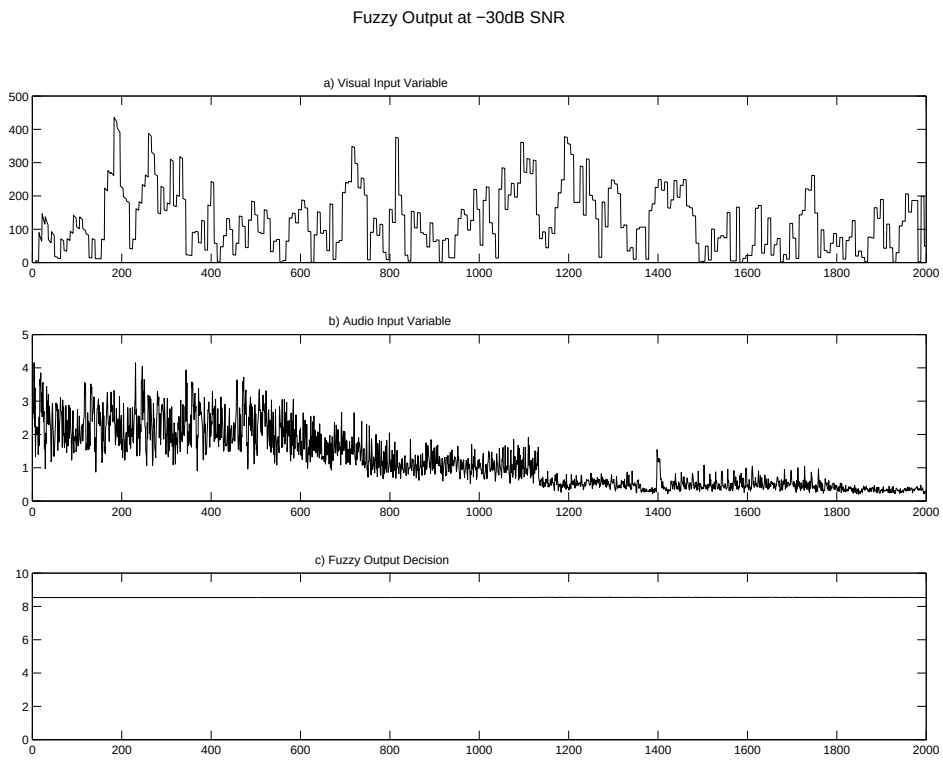


Figure 18: Fuzzy logic output decision depending on quality of visual information, for sentence with no frames considered to be of poor quality. (a) shows the input visual variable. It can be seen that all values are below 600, therefore every frame is considered to be good quality. (b) shows the audio input variable, with machine noise added to speech at an SNR of -30dB. (c) shows the fuzzy output processing decision.

5.4.2 Fuzzy Switching with Varying Visual Information

The previous examples considered a sentence with good quality visual information available at all times, but it was also considered to be of interest to observe the effect that varying the quality of visual information had on the fuzzy decision. If the audio input level was considered to be high, then the fuzzy logic system would use audiovisual processing, but only if the visual information was considered to be of good quality (i.e. the visual input fuzzy variable was low with all values below 600). To test this, a number of different sentences are compared, and the fuzzy outputs compared. These are shown in figures 18, 19, and 20. In all sentences, machine noise is mixed with the speech signal at a SNR of -30dB to ensure consistency.

In figure 18, (a) represents the visual input variable, (b) shows the audio input variable and (c) shows the fuzzy output decision. As can be seen, the visual information quality is considered to be good for all frames, and so audiovisual processing is chosen for all frames. However, figures 19, and 20 show different sentences with all other conditions kept the same. Despite the noise type and SNR being the same in each example, the visual input variable varies, and so the system only uses audiovisual processing when it is considered to be suitable. This demonstrates that the system adapts to different sentences and uses visual information in an appropriate manner.

5.4.3 Fuzzy Switching with Varying SNR Level

In addition to considering the effect of noise type and visual information, the effect of mixing the speech and noise sources at varying SNR levels is of interest. For this example, one sentence was chosen, with a small number of frames with poor quality visual information, and the noise source was the broadband machine noise. The sentences were then mixed at different SNR levels. Figure 21 shows the effect of mixing the sources at an SNR of -40dB.

In figure 21, (a) represents the mixed audio waveform, and (b) the associated fuzzy input variable. (c) Shows

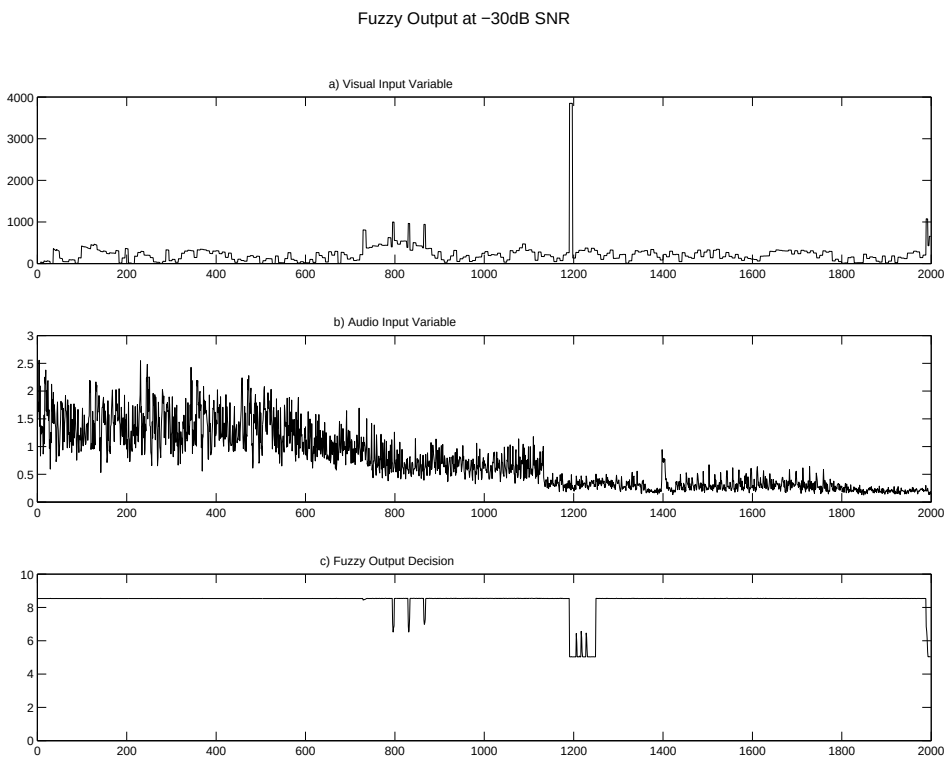


Figure 19: Fuzzy logic output decision depending on quality of visual information, for sentence with several frames considered to be of poor quality. (a) shows the input visual variable. It can be seen that there are a small number of frames where there is considered to be poor visual input. (b) shows the audio input variable, with machine noise added to speech at an SNR of -30dB. (c) shows the fuzzy output processing decision.

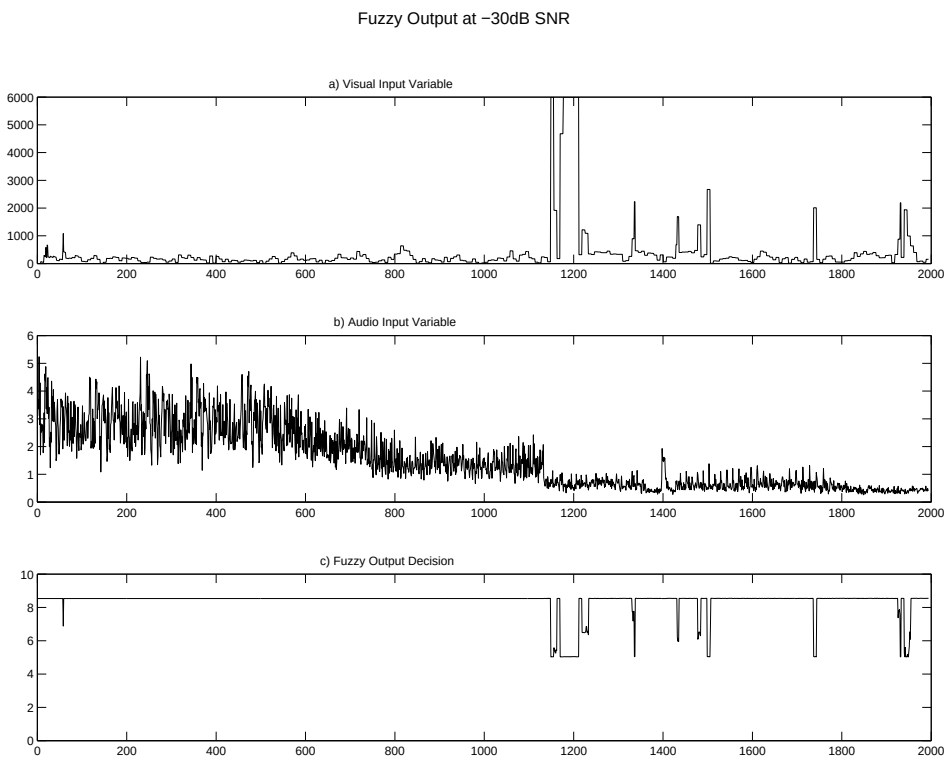


Figure 20: fuzzy logic output decision depending on quality of visual information, for sentence with several frames considered to be of poor quality. (a) shows the input visual variable. It can be seen that there are a number of frames where there is considered to be poor visual input. (b) shows the audio input variable, with machine noise added to speech at an SNR of -30dB. (c) shows the fuzzy output processing decision.

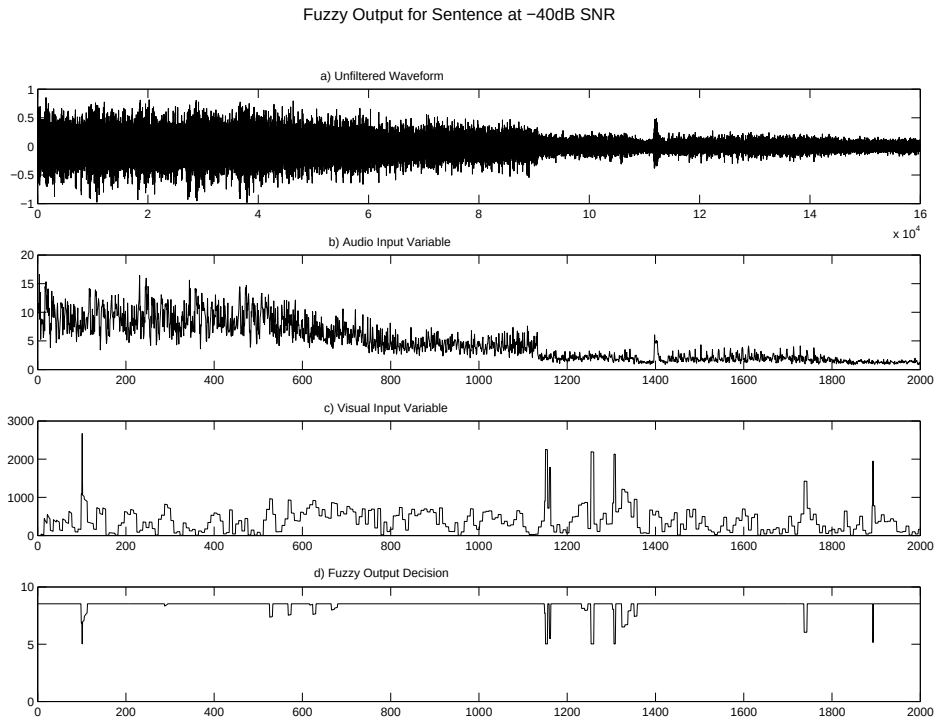


Figure 21: Fuzzy logic output decision depending on SNR level. (a) shows the input audio waveform, with speech and noise mixed at a SNR of -40dB. (b) shows the audio input variable. (c) shows the visual input variable, with a small number of frames considered to be of low quality. Finally, (d) shows the fuzzy output decision.

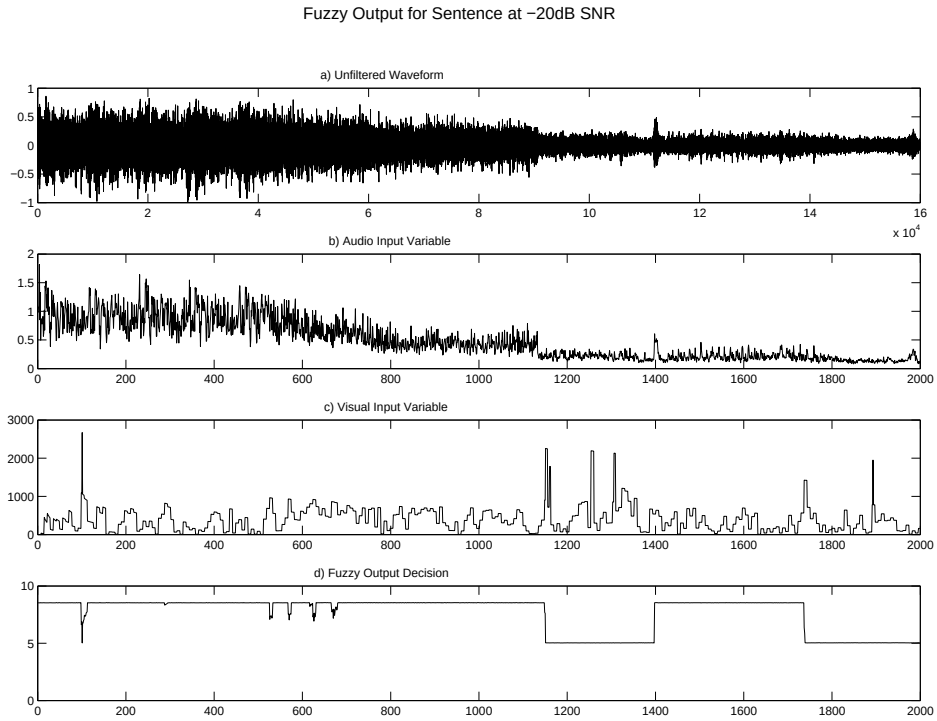


Figure 22: Fuzzy logic output decision depending on SNR level. (a) shows the input audio waveform, with speech and noise mixed at a SNR of -20dB. (b) shows the audio input variable. (c) shows the visual input variable, with a small number of frames considered to be of low quality. Finally, (d) shows the fuzzy output decision.

the visual input variable and (d) shows the fuzzy processing decision output. It can be seen that as the noise is considered to be consistently high, audiovisual information is used whenever good quality visual information is available. In figure 22, which shows the same sentence and noise mixture, but at a SNR of -20dB, there is a much more noticeable difference.

It can be seen in (a) that initially, the audiovisual processing option is chosen where appropriate. Later in this sentence, when there is considered to be lower quality visual information available, the system chooses audio-only processing. Unlike figure 21, the decision does not quickly change back to audiovisual processing, but continues to choose audio-only processing for a much greater number of frames. This is because of the increased SNR, demonstrating that the fuzzy logic system adapts to different noise inputs.

In figure 23, it can be seen in (a) that the speech is more visible in the waveform, which is a reflection on the increased SNR level. It can be seen in (d) that as the input level variable decreases, the fuzzy logic system chooses the audio-only option for much of the second part of the sentence, which is very different from previous examples of the same sentence with the same noise but a lower SNR. Finally, figure 24 shows that at a SNR of +10dB there are a much greater number of examples of the fuzzy logic system choosing to not filter the frame of speech. Overall, it is shown that the system will adapt to changing audio input levels, with an example of the same sentence, with the same visual input variable, and the same type of noise source, producing a different decision from frame-to-frame, depending on the SNR, and therefore the level of noise.

6 Discussion of Results

6.1 Fuzzy Input Variable Discussion

Section 5 presented an evaluation of the input variables, as while the audio level was a very simple and effective input detector, the visual quality and previous output detectors were more novel. It was concluded that the initial

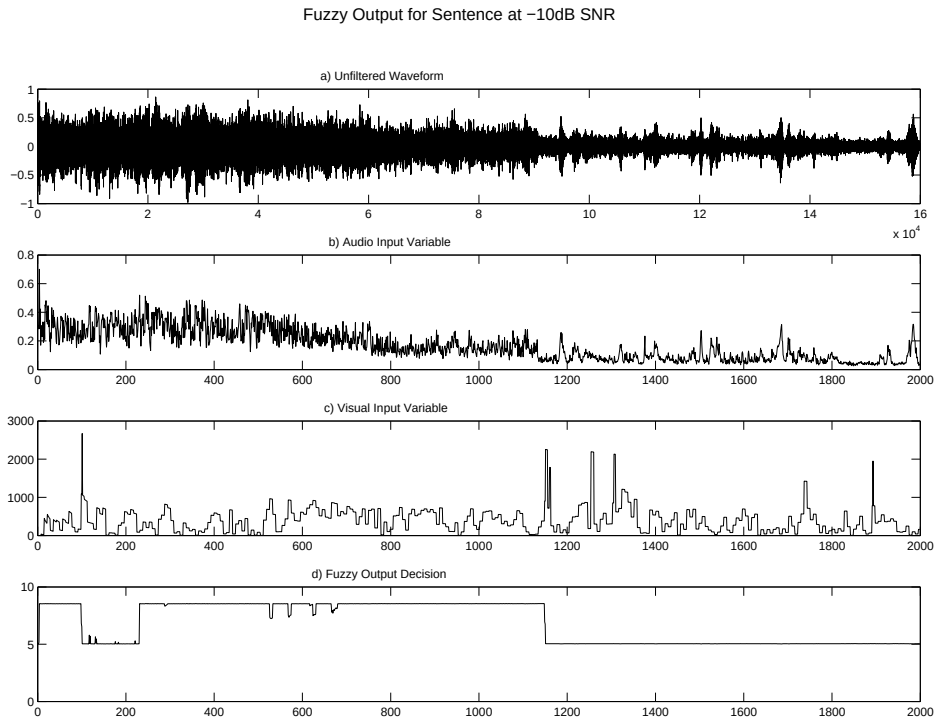


Figure 23: Fuzzy logic output decision depending on SNR level. (a) shows the input audio waveform, with speech and noise mixed at a SNR of -10dB. (b) shows the audio input variable. (c) shows the visual input variable, with a small number of frames considered to be of low quality. Finally, (d) shows the fuzzy output decision.

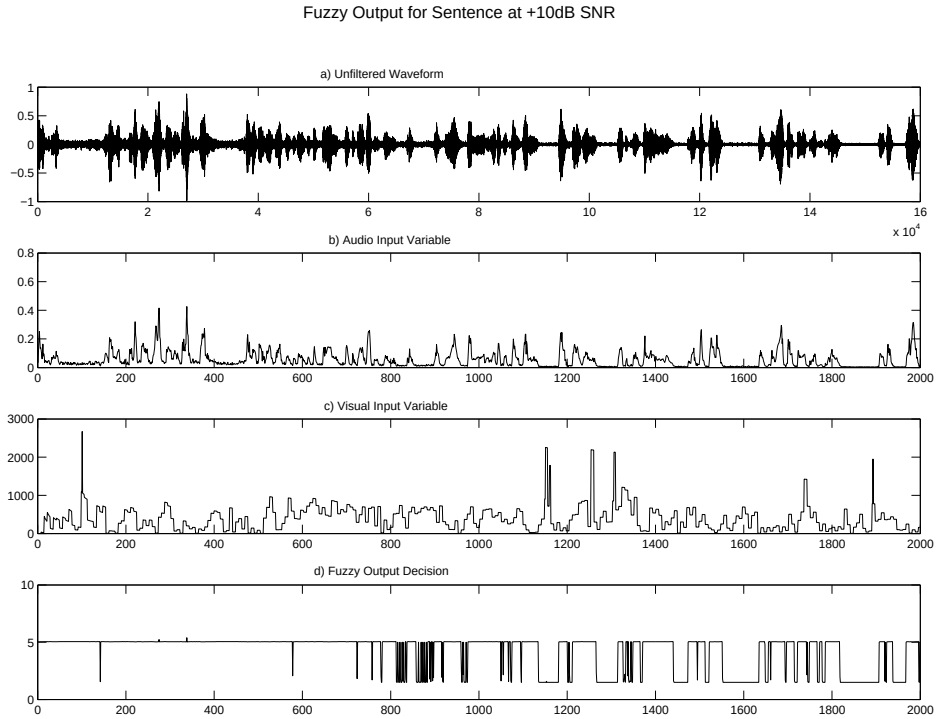


Figure 24: fuzzy logic output decision depending on SNR level. (a) shows the input audio waveform, with speech and noise mixed at a SNR of +10dB. (b) shows the audio input variable. (c) shows the visual input variable, with a small number of frames considered to be of low quality. Finally, (d) shows the fuzzy output decision.

visual fuzzy input variable can successfully be used to classify visual information. It was shown with a range of challenging conditions and widely varying conversation snippets from different speakers that the method correctly identified the quality of visual information in the majority of cases. Tracking errors due to animated movement of the speakers were generally correctly identified. This section justified the use of fuzzy variables by showing that different speech sentences had varying input values, matching the manually estimated predictions, and the chosen fuzzy thresholds were suitable to cover a wide range of potential input data.

However, there are further improvements that could be made to this approach. There are false positives present in the results. To improve the accuracy of the fuzzy input variable, it could be possible to create an improved input variable using a machine learning technique, such as HMMs or ANNs, which would use a more sophisticated assessment of whether the input value is a partial lip region, correct full ROI, or not a match. Due to the low error rate the present implementation of this detector is considered to be suitable for use as part of a future refinement of this system.

Section 5 also discussed the use of the previous frame fuzzy output value as an input for the subsequent frame. The aim this is to reduce rapid switching between processing options on a frame-by-frame basis. The potential benefit of using the single previous frame or a floating mean of 3, 5, and 10 previous outputs was investigated. The results showed that although using a floating mean smoothed the input variable on a frame-to-frame basis, it made very little difference to the final fuzzy output value, justifying the use of a single frame for the sake of simplicity.

The effect of using the fuzzy variable on switching of processing options from frame-to-frame was also evaluated. While it is expected that the processing option will change in response to environmental conditions, rapid oscillation should be prevented where possible. To investigate this, the fuzzy rules pertaining to the previous input variable were disabled and the system was run with a number of sentences at different SNR levels. The results, when compared to running the system with the rules enabled demonstrated that using the previous variable fulfilled the requirement of reducing the oscillation from frame-to-frame.

However, there are a number of ways in which these inputs could be improved. As discussed above, a model could be trained to accurately identify the quality of an image. Also, in addition to the relatively basic audio level input, additional detectors such as a VAD could be used to positively identify the presence or absence of speech. This would serve as an additional input into the fuzzy-based system (and so would require the writing of additional rules), as used in some current commercial hearing-aids. This could also include specific front-back or wind detectors, to add versatility to the system.

6.2 Fuzzy Switching System Performance Evaluation

The fuzzy-based system performs as expected. The system switches between processing options when considered appropriate, as confirmed by the results in section 5. Firstly, with regard to the audio output of the system, it can be seen from the evaluation that the results are of limited interest. The audiovisual filtering often produces a significantly worse result than using beamforming. This was an issue also identified in a previous paper [1], where the result was found to be significantly worse when used with data not similar to that which the system had not previously been trained with.

The fuzzy output results are of interest because they demonstrate that the fuzzy-based system performs as expected. At a very low SNR, the system makes use of the audiovisual processing option, and at a high SNR, the system predominantly makes use of the audio-only approach as expected. However, at even the lowest SNR, the objective and subjective scores are not identical to the audiovisual scores. This is because the fuzzy-based approach makes use of different processing options, depending on the fuzzy input variables, and so there is a difference in scores. A similar pattern can be seen at a higher SNR, when the audio-only approach is predominantly used, but again, it is not used in all cases, and is dependent on the input fuzzy variables. However, the score is again rated as lower than the beamforming approach.

This would initially suggest that the beamforming approach is always better; however, this result has to be interpreted with a degree of caution. Previous work by the authors [1] discussed the results of objective tests when using an inconsistent clapping noise with transients and silences, designed to be extremely challenging for a beamformer. In this scenario, it was found that the audio-only approach produced no results of value. However, the audiovisual approach also performed poorly, due to the limitations with the training dataset discussed previously. Accordingly, although the fuzzy-based approach performed as expected, the limitations identified with the speech processing techniques also show that the system is currently only suitable for testing in specialised environments, and needs further development before being suitable for more general purpose use.

Despite the limitations identified above, an investigation of the performance of the fuzzy switching system has shown that the system switches between inputs as expected. In noisy environments with a high SNR, the system

automatically selects a different form of processing (in this case audiovisual), but only when there is suitable associated visual information. This demonstrates that the system is capable of adapting to a range of different audiovisual environments, and is capable of solving the problem of lack of availability of visual information. It should be emphasised that this is a preliminary system, and future work specifically with regard to this aspect of the system would investigate the processing cost of using such a system, and potential performance savings to be gained from using different processing options, and improving the speech processing techniques used in order to improve versatility.

Overall, despite positive switching results, in order to improve this system, it is clear that the audiovisual filtering approach needs to be improved and refined. The results show that there is considerable scope for improvement when using data that the system has not been trained with. This limitation explains the limited speech evaluation results. Another significant improvement needed is to further develop the system to enable more accurate evaluation. The results showed that the beamforming results were good with the appropriate type of noise, but extremely limited with an unsuitable noise, and so therefore had to be treated with caution. Future work would involve the development of this system to be able to use a true multi-microphone environment rather than a simulated room, to fully and accurately evaluate the system. This would involve further refinement, and also the acquisition of improved hardware to use for testing. This improved hardware would allow for improved data synchronisation, correct acquisition of impulse responses and directional information, and would allow for noise to be added during recording rather than afterwards, taking more account of the Lombard Effect.

7 Conclusion

This paper expanded on an initial concept of a two stage audio-visual system presented in previous work by the authors [1], to present a cognitively inspired multimodal speech filtering approach. This approach was designed to overcome limitations identified with a previous iteration of this system, and was inspired by the multimodal nature of human speech perception. To perform the enhancement, both audio-only beamforming and visually derived Wiener filtering were utilised to filter speech, within a fuzzy logic based framework. This framework uses a number of level detectors to determine the quality of the input information (i.e. whether a lip image of adequate quality is present in a frame of visual data), and also what level of energy is present in a frame of audio data. These detectors determine the appropriate processing method to use to filter a frame of noisy speech on a frame-by-frame basis.

All aspects of the system were thoroughly tested using a custom recorded novel speech database. This corpus contained audiovisual speech data of variable quality, with an emphasis on natural conversational communication, encouraging the speakers to move naturally and engage in emotional speech. This meant that the visual data intentionally had some quality issues due to the speakers moving around, covering their mouth, speaking in different manners, and turning their heads. It can be seen from the results presented in this paper that the chosen fuzzy inputs functioned well. The visual quality input accurately evaluated the quality of the visual information and could identify whether the ROI input was a good quality lip image. The level detector functioned as expected, and in addition, the previous frame output was shown to smooth the oscillation between frames that could be caused by audio and visual inputs close to the fuzzy thresholds. In addition to the detectors, the output from the fuzzy system was tested and while the audio output did not perform well due to the visual component of the system not being trained with the novel corpus used in this work. It was considered that although the system could be trained to gain some small improvements in performance, a more productive approach would be to improve the visual derived filtering component in future work. However, a thorough evaluation of the switching process showed that the fuzzy based system functioned well, with the processing decision changing depending on the input detectors.

While the cognitively inspired switching framework has been shown in this paper to perform successfully, and overcomes one of the weaknesses presented in initial work [1], there are further refinements that could be performed within the overall fuzzy switching framework. Although the GMM-GMR based approach utilised in this paper can deliver positive results, it does not perform well when presented with data significantly different from that it has been trained with. This was also found to be the case in the previous work. Although this is a common problem for multimodal speech filtering systems, this is an aspect which requires improvement with the upgrading of the audiovisual speech model presently used in this system. Future work with regard to this cognitively inspired system is to improve the relatively unsophisticated visually derived speech estimation model. It has been shown that although the switching performance is good, the visually derived filtering algorithm itself does not perform well with novel data, and so this aspect of the overall framework is a prime candidate for consideration with regard to improvement. Overall, the benefits of making use of visual information as part of a

cognitively inspired speech enhancement switching framework are clear.

References

[1] A. Abel and A. Hussain, "Novel two-stage audiovisual speech filtering in noisy environments," *Cognitive Computation*, pp. 1–18, 2013.

[2] J. Greenberg, "Improved design of microphone-array hearing aids," 1994.

[3] R. Zelinski, "A microphone array with adaptive post-filtering for noise reduction in reverberant rooms," in *Acoustics, Speech, and Signal Processing, 1988. ICASSP-88., 1988 International Conference on*, pp. 2578–2581, 1988.

[4] A. Hussain, S. Cifani, S. Squartini, F. Piazza, and T. Durrani, "A Novel Psychoacoustically Motivated Multichannel Speech Enhancement System," *Verbal and Nonverbal Communication Behaviours*, pp. 190–199, 2007.

[5] L. Yang, J. Lv, and Y. Xiang, "Underdetermined blind source separation by parallel factor analysis in time-frequency domain," *Cognitive computation*, pp. 1–8, 2013.

[6] S. Gannot, D. Burshtein, and E. Weinstein, "Signal enhancement using beamforming and nonstationarity with applications to speech," *IEEE Transactions on Signal Processing*, vol. 49, no. 8, pp. 1614–1626, 2001.

[7] L. Griffiths and C. Jim, "An alternative approach to linearly constrained adaptive beamforming," *IEEE Transactions on Antennas and Propagation*, vol. 30, no. 1, pp. 27–34, 1982.

[8] N. Wiener, *Extrapolation, interpolation, and smoothing of stationary time series: with engineering applications*. The MIT Press, 1949.

[9] J. Li, S. Sakamoto, S. Hongo, M. Akagi, Y. Suzuki, *et al.*, "A two-stage binaural speech enhancement approach for hearing aids with preserving binaural benefits in noisy environments," *Journal of the Acoustical Society of America*, vol. 123, no. 5, pp. 3012–3012, 2008.

[10] J. Li, S. Sakamoto, S. Hongo, M. Akagi, and Y. Suzuki, "Two-stage binaural speech enhancement with Wiener filter for high-quality speech communication," *Speech Communication*, 2010.

[11] T. Van den Bogaert, S. Doclo, J. Wouters, and M. Moonen, "Speech enhancement with multichannel Wiener filter techniques in multimicrophone binaural hearing aids," *The Journal of the Acoustical Society of America*, vol. 125, pp. 360–371, 2009.

[12] M. Anderson, T. Adali, and X.-L. Li, "Joint blind source separation with multivariate gaussian model: algorithms and performance analysis," *Signal Processing, IEEE Transactions on*, vol. 60, no. 4, pp. 1672–1683, 2012.

[13] B. Rivet, L. Girin, and C. Jutten, "Mixing Audiovisual Speech Processing and Blind Source Separation for the Extraction of Speech Signals From Convolutive Mixtures," *IEEE Transactions on Audio, Speech and Language Processing*, vol. 15, no. 1, pp. 96–108, 2007.

[14] B. Rivet and J. Chambers, "Multimodal speech separation," in *Advances in Nonlinear Speech Processing* (J. Sole-Casals and V. Zaiats, eds.), vol. 5933 of *Lecture Notes in Computer Science*, pp. 1–11, Springer Berlin / Heidelberg, 2010.

[15] B. Rivet, L. Girin, and C. Jutten, "Log-rayleigh distribution: A simple and efficient statistical representation of log-spectral coefficients," *IEEE transactions on audio, speech, and language processing*, vol. 15, no. 3, pp. 796–802, 2007.

[16] W. Sumby and I. Pollack, "Visual contribution to speech intelligibility in noise," *Journal of the Acoustical Society of America*, vol. 26, no. 2, pp. 212–215, 1954.

[17] N. P. Erber, "Auditory-visual perception of speech," *Journal of Speech and Hearing Disorders*, vol. 40, no. 4, p. 481, 1975.

[18] Q. Summerfield, "Use of visual information for phonetic perception," *Phonetica*, vol. 36, no. 4-5, pp. 314–331, 1979.

[19] F. Berthommier, "A phonetically neutral model of the low-level audio-visual interaction," *Speech Communication*, vol. 44, no. 1, pp. 31–41, 2004.

[20] H. McGurk and J. MacDonald, "Hearing lips and seeing voices," *Nature*, vol. 264, pp. 746–748, 1976.

[21] M. L. Patterson and J. F. Werker, "Two-month-old infants match phonetic information in lips and voice," *Developmental Science*, vol. 6, no. 2, pp. 191–196, 2003.

[22] M. L. Patterson and J. F. Werker, "Matching phonetic information in lips and voice is robust in 4.5-month-old infants," *Infant Behavior and Development*, vol. 22, no. 2, pp. 237–247, 1999.

[23] A. A. Ghazanfar, K. Nielsen, and N. K. Logothetis, "Eye movements of monkey observers viewing vocalizing conspecifics," *Cognition*, vol. 101, no. 3, pp. 515–529, 2006.

[24] J.-L. Schwartz, F. Berthommier, and C. Savariaux, "Seeing to hear better: evidence for early audio-visual interactions in speech identification," *Cognition*, vol. 93, no. 2, pp. B69–B78, 2004.

[25] K. W. Grant and P.-F. Seitz, "The use of visible speech cues for improving auditory detection of spoken sentences," *The Journal of the Acoustical Society of America*, vol. 108, p. 1197, 2000.

[26] J. Kim and C. Davis, "Testing the cuing hypothesis for the av speech detection advantage," in *AVSP 2003-International Conference on Audio-Visual Speech Processing*, 2003.

[27] L. E. Bernstein, S. Takayanagi, and E. T. Auer Jr, "Enhanced auditory detection with av speech: Perceptual evidence for speech and non-speech mechanisms," in *AVSP 2003-International Conference on Audio-Visual Speech Processing*, 2003.

[28] K. W. Grant, "The effect of speechreading on masked detection thresholds for filtered speech," *The Journal of the Acoustical Society of America*, vol. 109, p. 2272, 2001.

[29] K. S. Helfer and R. L. Freyman, "The role of visual speech cues in reducing energetic and informational masking," *The Journal of the Acoustical Society of America*, vol. 117, p. 842, 2005.

[30] F. Wightman, D. Kistler, and D. Brungart, "Informational masking of speech in children: Auditory-visual integration," *The journal of the Acoustical Society of America*, vol. 119, p. 3940, 2006.

[31] D. Sodoyer, B. Rivet, L. Girin, C. Savariaux, J.-L. Schwartz, and C. Jutten, "A study of lip movements during spontaneous dialog and its application to voice activity detection," *The Journal of the Acoustical Society of America*, vol. 125, no. 2, pp. 1184–1196, 2009.

[32] H. Yehia, P. Rubin, and E. Vatikiotis-Bateson, "Quantitative association of vocal-tract and facial behavior," *Speech Communication*, vol. 26, no. 1-2, pp. 23–43, 1998.

[33] J. Barker and F. Berthommier, "Estimation of speech acoustics from visual speech features: A comparison of linear and non-linear models," in *AVSP'99-International Conference on Auditory-Visual Speech Processing*, 1999.

[34] I. Almajai and B. Milner, "Maximising audio-visual speech correlation," in *Proc. AVSP*, 2007.

[35] S. Cifani, A. Abel, A. Hussain, S. Squartini, and F. Piazza, "An investigation into audiovisual speech correlation in reverberant noisy environments," in *Cross-Modal Analysis of Speech, Gestures, Gaze and Facial Expressions: COST Action 2102 International Conference Prague, Czech Republic, October 15-18, 2008 Revised Selected and Invited Papers*, vol. 5641, pp. 331–343, Springer-Verlag, 2009.

[36] A. Abel, A. Hussain, Q. Nguyen, F. Ringeval, M. Chetouani, and M. Milgram, "Maximising audiovisual correlation with automatic lip tracking and vowel based segmentation," in *Biometric ID Management and Multimodal Communication: Joint COST 2101 and 2102 International Conference, BioID_MultiComm 2009, Madrid, Spain, September 16-18, 2009, Proceedings*, vol. 5707, pp. 65–72, Springer-Verlag, 2009.

[37] L. Girin, J. Schwartz, and G. Feng, "Audio-visual enhancement of speech in noise," *The Journal of the Acoustical Society of America*, vol. 109, p. 3007, 2001.

[38] R. Goecke, G. Potamianos, and C. Neti, "Noisy audio feature enhancement using audio-visual speech data," in *Acoustics, Speech, and Signal Processing, 2002. Proceedings.(ICASSP'02). IEEE International Conference on*, vol. 2, pp. 2025–2028, IEEE, 2002.

[39] G. Potamianos, C. Neti, and S. Deligne, "Joint Audio-Visual Speech Processing for Recognition and Enhancement," in *AVSP 2003-International Conference on Auditory-Visual Speech Processing*, pp. 95–104, 2003.

[40] I. Almajai and B. Milner, "Enhancing Audio Speech using Visual Speech Features," in *Proc. Interspeech, Brighton, UK*, 2009.

[41] Q. Nguyen and M. Milgram, "Semi adaptive appearance models for lip tracking," in *ICIP09*, pp. 2437–2440, 2009.

[42] S. Calinon, F. Guenter, and A. Billard, "On learning, representing, and generalizing a task in a humanoid robot," *IEEE Transactions on Systems, Man, and Cybernetics, Part B*, vol. 37, no. 2, pp. 286–298, 2007.

[43] I. Almajai and B. Milner, "Effective visually-derived Wiener filtering for audio-visual speech processing," in *Proc. Interspeech, Brighton, UK*, 2009.

[44] N. Tellier, H. Arndt, and H. Luo, "Speech or noise? using signal detection and noise reduction," *Hearing Review*, vol. 10, no. 6, pp. 48–51, 2003.

[45] A. Esposito, E. Ezin, and C. Reyes-Garcia, "Designing a fast neuro-fuzzy system for speech noise cancellation," *MICAI 2000: Advances in Artificial Intelligence*, pp. 482–492, 2000.

[46] K. Chung, "Challenges and recent developments in hearing aids. part i. speech understanding in noise, microphone technologies and noise reduction algorithms," *Trends Amplif*, vol. 8, no. 3, pp. 83–124, 2004.

[47] M. El-Wakdy, E. El-Sehely, M. El-Tokhy, A. El-Hennawy, N. Mastorakis, V. Mladenov, Z. Bojkovic, D. Simian, S. Kartalopoulos, A. Varonides, *et al.*, "Speech recognition using a wavelet transform to establish fuzzy inference system through subtractive clustering and neural network(anfis)," in *WSEAS International Conference. Proceedings. Mathematics and Computers in Science and Engineering*, no. 12, WSEAS, 2008.

[48] L. Zadeh, "Fuzzy sets*," *Information and control*, vol. 8, no. 3, pp. 338–353, 1965.

[49] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in *Computer Vision and Pattern Recognition, IEEE Computer Society Conference on*, vol. 1, pp. 511–518, IEEE Comput. Soc, 2001.

[50] D.-J. Kroon, "Viola jones object detection." http://www.mathworks.com/matlabcentral/fileexchange/29437-viola-jones-object-detection, 2010.

[51] A. Bagis, "Determining fuzzy membership functions with tabu search–an application to control," *Fuzzy sets and systems*, vol. 139, no. 1, pp. 209–225, 2003.

[52] C. Sanderson, *Biometric person recognition: Face, speech and fusion*. VDM Verlag Dr. Muller, 2008.

[53] M. Cooke, J. Barker, S. Cunningham, and X. Shao, "An audio-visual corpus for speech perception and automatic speech recognition," *The Journal of the Acoustical Society of America*, vol. 120, no. 5 Pt 1, pp. 2421–2424, 2006.

[54] Y. Hu and P. Loizou, "Evaluation of objective quality measures for speech enhancement," *IEEE Transactions on Audio, Speech and Language Processing*, vol. 16, no. 1, pp. 229–238, 2008.

[55] Y. Lu and P. Loizou, "A geometric approach to spectral subtraction," *Speech communication*, vol. 50, no. 6, pp. 453–466, 2008.