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RECOGNIZING FACIAL EXPRESSION THROUGH FREQUENCY NEURAL NETWORK

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Abstract - An accurate and robust transformed face descriptor that exploits the capabilities of filtered back projection applied on Fourier filter Transform (FFT) and kernel frequency neural network (FreNet) methods is proposed. The method is invariant to rotation, variations in facial expression and illumination. Filtered back projection constructs transform parameters from a set of projections through an image enhancing feature patterns that provide an initialization for subsequent FFT computations. FFT discards high-frequency coefficients that form least significant data to retain a subset of lower frequency coefficients visually significant in the image. The resulting coefficient features are mapped to lower dimensional space using frequency neural network (FreNet) which extracts principal components that form the basis for the neural network classifier. Experiments were carried on JAFEE database and computed results compared with FRENET and FFT approach. The results demonstrate significant improvements in results compared to other approaches.

Keywords: Facial expression, fast Fourier transform, keras, polling layer, multiplication layer, Fan Fiction network, Deep learning, Unified modeling language, block sub sampling, kernel, recognition.

1.INTRODUCTION

FACIAL expression is a significant non-verbal approach for humans to convey information in communication. As a branch of pattern recognition, it has a great value in the field of human-computer interaction, computer vision and psychology. Research of facial expression recognition (FER) intends to enable a machine to recognize facial expression automatically. Expressions (anger, fear, disgust, surprise, happiness and sadness) that are universally expressed on the human face. So far, there have been many studies focusing on the recognition of these facial expressions. Existing facial features of FER can be divided into two categories: handcrafted feature and learned feature. The design of useful handcrafted feature relies on domain knowledge, which requires a heavy workload to be carried out manually. Compared with the methods based on handcrafted feature, deep learning has achieved superior performance on feature learning. Therefore, there are many convolutional neural network (CNN) based deep learning methods for FER. However, a complex CNN involves huge computational costs caused by a large number of convolutions, which has high requirements on hardware devices In the meanwhile, existing facial features of FER can be divided into another two categories according to different domains: spatial domain and frequency domain. In the spatial domain, facial features can be calculated based on geometry and image gradient. In the frequency domain, the high-frequency components correspond to noises and edges. On the contrary, the low-frequency components are comprehensive measurement of image intensity. Hence, image features can be calculated based on frequency analysis. In traditional image processing, frequency domain processing is of great significance such as efficient computation and spatial redundancy elimination. In general, the number of FER researches in spatial domain far exceeds that in frequency domain. To our best knowledge, existing methods in frequency domain all adopted handcrafted feature and FER has not been addressed by frequency based deep learning method yet. The above insights inspire us to exploit the advantages of processing image in frequency domain and develop a frequency based deep learning model for FER. Motivated by this, this paper proposes a frequency neural network (FreNet) for FER. First, we propose a learnable multiplication kernel (LMK) which works as an efficient filter to learn facial features in frequency domain. Based on the LMK, we construct multiple multiplication layers for feature learning. Second, a summarization layer is proposed following multiplication layers to further yield high-level features. Third, based on the property of Fourier filter transform (FFT), we perform critical information extraction (CIE) for straightforward dimension reduction, and utilize the proposed layers to

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construct the Basic-FreNet, which can yield high-level feature on the widely used FFT feature. Basic-FreNet, we propose a better framework: Block-FreNet in which the weight-shared LMK and block sub-sampling (BSS) are designed. Finally, we conduct experiments on four well-known expression datasets, and the experimental result shows that our models have the ability of learning feature in frequency domain for FER and achieve superior performance with lightweight calculation. Our main contributions can be summarized as follows: We propose a novel frequency based deep learning approach for FER. To our best knowledge, it is the first attempt to fill in the blank of frequency based deep learning model forFER. We propose the LMK and construct multiplication layers for feature learning in frequency domain. The multiplication layers can learn features on the widely used handcrafted feature: upper-left FFT coefficients and obtain high-level features. • We propose the summarization layer following the multiplication layer to further yield high-level features, which improves discriminability of the learned feature and provides better performance. It propose the Block- FreNet,in which the weight-shared LMK is designed for feature learning and the BSS is designed for dimension reduction in frequency domain, to further achieve better performance.

2.AIM

Facial expression recognition has become a newly-emerging topic in recent decades, which has important value in the field of human-computer interaction. Analysis the emotional expressions of human being. Facial expression recognition is the task of classifying the expressions on face images into various categories such as angry, fear, sad, happy etc,.

3. SYSTEM ANALYSIS

Systemanalysisistheoverallanalysisofthesystembeforeimplementation and for arriving at a precise solution. Careful analysis of a system before implementation prevents post implementation problems that might arise due to bad analysis of the problem statement. Thus the necessity for systems analysis is justified. Analysis is the first crucial step, detailed study of the various operations performed by a system and their relationships within and outside of the system . Analysis is defining the boundaries of the system that will be followed by design and implementation.

3.1 EXISTING SYSTEM

In existing work, presents a deep learning based approach, named Frequency neural network (FreNet), for facial expression recognition. Based on the property of Fourier filter transform (FFT), it utilize multiplication layers and summarization layer to construct the Basic- FreNet, which can yield high-level features on the widely used FFT feature. Finally, to further achieve better performance on Basic- FreNet, it proposed the Block- FreNet in which the weight-shared multiplication kernel is designed for feature learning and the block sub-sampling is designed for dimension reduction. The experimental results show that the Block- FreNet not only achieves better performance.

Disadvantages

i) High Computation cost is required for recognition.
ii) Requires more memory to store the Transformed frames.

3.2 PROPOSED SYSTEM

The proposed work presents a deep learning based approach, named frequency neural network (FreNet), for facial expression recognition. Different from convolutional neural network in spatial domain, FreNet inherits the advantages of processing image in frequency domain, such as efficient computation and spatial redundancy elimination. First, we propose the learnable multiplication kernel and construct multiple multiplication layers to learn features in frequency domain. Second, a summarization layer is proposed following multiplication layers to further yield high-level features. Third, based on the property of Fast Fourier transform (FFT), we utilize multiplication layers and summarization layer to construct the Basic- FFNet, which can yield high-level features on the widely used FFT feature. Finally, to further achieve better performance on Basic- FFNet, we propose the Block- FFNet in which the weight-shared multiplication kernel is designed for feature learning and the block sub-sampling is designed for dimension reduction. The experimental results show that the Block- FFNet not only achieves superior performance, but also greatly reduces the computational cost. To our best knowledge, the proposed approach is the first attempt to fill in the blank of frequency based deep learning model for facial expression recognition.

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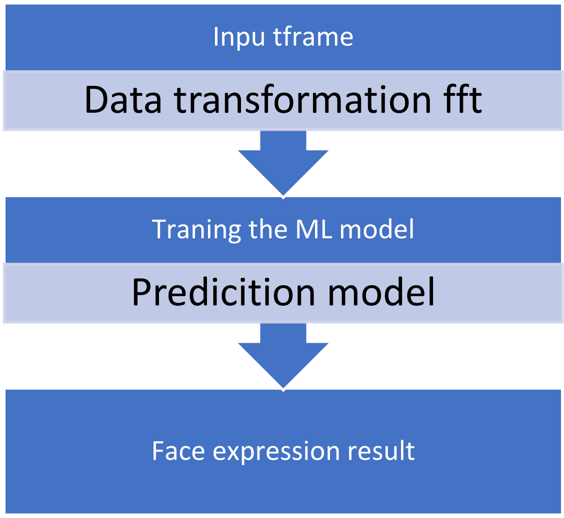
ADVANTAGES

i) Less Computation cost is required for recognition.
ii) Requires less memory to store the Transformed frames.
iii) Fast transformation of input frames



4. SYSTEM IMPLEMENTATION

Implementation is the stage in the project where the theoretical design is turned into a working system. The implementation phase constructs, installs and operates the new system. The most crucial stage in achieving a new successful system is that it will work efficiently and effectively.
There are several activities involved while implementing a new project.

i) Enduser Training
ii) Enduser Education
iii) Training on the application software

All projects go through a life cycle beginning with defining how the new software package will be used in your organization (requirements) through the end point of the project–a successful and effective implementation. Our activities matrix has been organized around six generic implementation life cycle phases.

1) Business Requirement and Proposed Solution – this is the phase where your business requirements are finalized, the software package is learned, and a solution using the package is defined to meet the business requirements.
2) High Level Design(Functional Specifications)–the plannedsolution is further clarified by functionally specifying how the system will operation.
3) System Implementation – in this phase the system is implemented and operations are converted to the new system.
4) System Support and Maintenance – this is the post implementation phase where the system is turned over to the normal support and maintenance process. Most organizations use a standard development life cycle that they use when building or customizing systems.

5.SYSTEM DESIGN

System design concentrates on moving from problem domain to solution domain. This important phase is composed of several steps. It provides the understanding and procedural details necessary for implementing the system recommended in the feasibility study. Emphasis is on translating the performance requirements in to design specification. The design of any software involves mapping of the software requirements in to Functional modules. Developing are al time application or any system utilities involves two processes. The first process is to design the system to implement it. The second is to construct the executable code. Software design is a first step in the development phase of the software life cycle.Before design the system user requirements have been identified, information has been gathered to verify the problem and evaluate the existing system. A feasibility study has been conducted to review alternative solution and

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provide cost and benefit justification. To overcome this proposed system is recommended. At this point the design phase begins.The process of design involves conceiving and planning out in the mind and making a drawing .In software design, there are three distinct activities

5.1 DATA FLOW DIAGRAM

The Data Flow Diagram is a graphical model showing the inputs, processes, storage & outputs of a system procedure in structure analysis. A DFD is also known as a Bubble Chart. The Data flow diagram provides additional information that is used during the analysis of the information domain, and server as a basis for the modelling of functions. The description of each function presented in the DFD is contained is a process specification called as PSPEC.

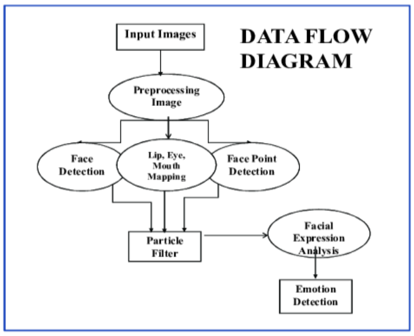

Figure : Data Flow Diagram

5.2 SYSTEMARCHITECTURE

An architectural diagram is a diagram of a system that is used to abstract the overall outline of the software system and the relationships, constraints, and boundaries between components. It is an important tool as it provides an overall view of thephysical deployment of the software system and its evolution roadmap.

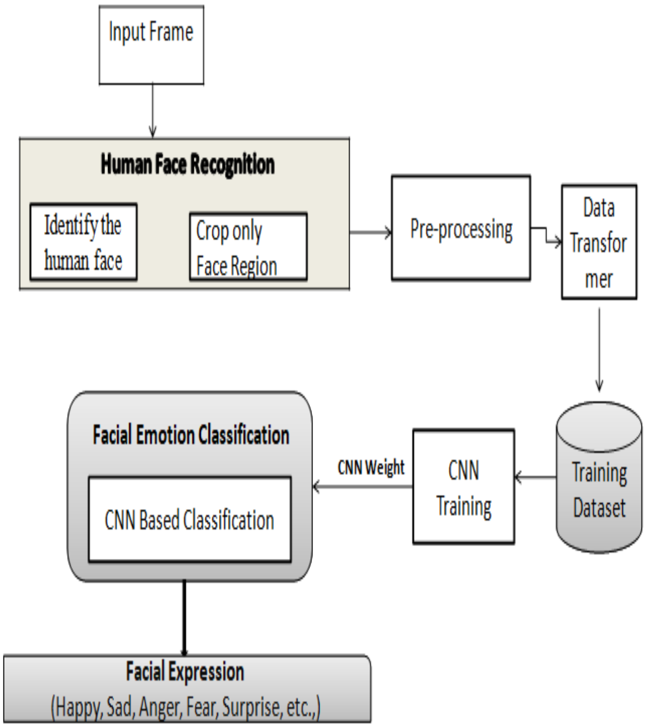

Figure : System Architecture

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7. SOFTWARE REQUIREMENTS

Tools : Spyder(python)

8. MODULES DESCRIPTION

Design is concerned with identifying software components specifying relationship among components. Specifying software structure and providing blue print for the document phase. Modularity is one of the desirable properties of large systems.
Implementation is the stage of the project when the theoretical design is turned out into a working system. Thus it can be considered to be the most critical stage in achieving a successful new system and in giving user, confidence that the new system will work and be effective.

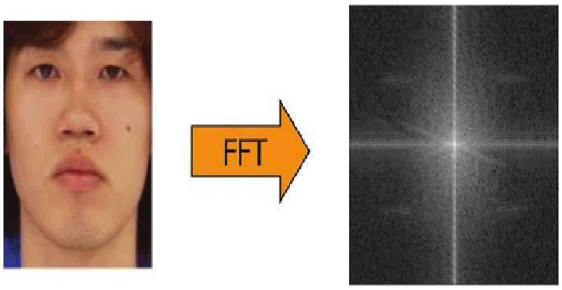
The modules are
i) Pre-processing & FFT Transformation
ii) FFNet Construction
iii) FFNet Training
iv) Face Expression Detection

9.CONCLUSION

In this paper, we propose a novel deep learning study convolutional neural network for FER. Based on the characteristic of convolutional neural network l we propose the and construct multiplication layers for feature learning. Then we propose the summarization layer to further yield high-level features. Based on the proposed techniques, we first utilize the energy compaction property of Scalar/Vector and construct the Basic-CNN. Then, we propose the weight-shared CNN for feature learning and the BSS for dimension reduction in frequency domain to construct the Block-CNN. The results of FER show that our models have the ability of learning features in frequency domain and predicting facial expression. Furthermore, the ablation study and parameter analysis demonstrate the effectiveness of the proposed techniques.

RESULT

Magnitude convolution is an operation which takes two functions as input , and produces a single function output .



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