Adaptive Human Motion Estimation Filter with Integrated Phase Compensator

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Abstract
In this paper, human motion analysis is studied and forms one of the key tasks to understand the 2D video image estimation. An adaptive human motion estimation filter is proposed to extract the features from the human motion information through video samples. We also identified the different trained weights values in both low and high frequency human motion estimation. The main objective of an adaptive motion estimation filter is to explore the video patterns efficiently and significantly. The phase shift compensator is identified and integrated to compensate the phase shift in the estimated human motion at higher frequency.

Key words: *Human motion estimation, 2Dimensional feature extraction, Motion Tracking, Phase Compensation.*

1. Introduction

The human motion analysis is a conventional approach to design and identify the video image sequence as static image sequence for detecting and analyzing human motion in real time. The human motion activities are recognized by a machine to interact intelligently and effortlessly with a human-inhabited environment. This approach is well established for identifying the images, speech, and video samples that are recognized from 2D images. The motion estimation filter (MEF) is introduced to reduce the invariance in the 2D images. The performance evaluation of human motion system is estimated using the MEF algorithm. This algorithm is identified to track and recognize the visual constraints in the real world videos with the combination of generative and discriminative models in a filtering framework can improve the normalization, selection and detection of visual attention. The MEF algorithm realizes a deterministic approach to track any 2D-features representable in a real time application.

2. Design of Adaptive Motion Estimation Filter (MEF)

The adaptive scheme for human motion estimation is designed in two blocks namely;

Block – I (refer Figure 1): This operates on the human motion input in the presence of noise and facilitate the extraction of the correlated samples using down sampler and unit delay elements.

Block – II (refer Figure 2): This consists of unsupervised network training stage and using the trained weights perform noise separation and constitutes the human motion estimation (MEF).

2.1 Correlation Extractor

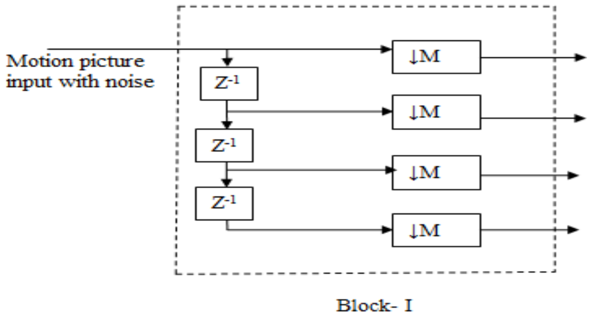
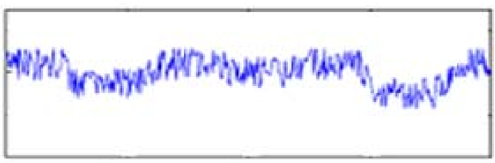


Fig.1 Correlation Extractor Module

Note $\boxed{\downarrow M}$ down sampler & z^{-1} delay by unit sample.

2.1.1 Implementation results of Correlation extractor

The output of block-I consists of the motion picture samples corresponding to $\sum_{n=0}^{N} x(4n)$, $\sum_{n=0}^{N} x(4n+1)$, $\sum_{n=0}^{N} x(4n+2)$ and $\sum_{n=0}^{N} x(4n+3)$ respectively. The correlation present among the different delayed samples i.e. x (n) to x (n-k) for k=1 to 3, of the human motion video input is depicted in Figure 2(a) and 2(b) for both Low Frequency and (ii) High Frequency Motion respectively.



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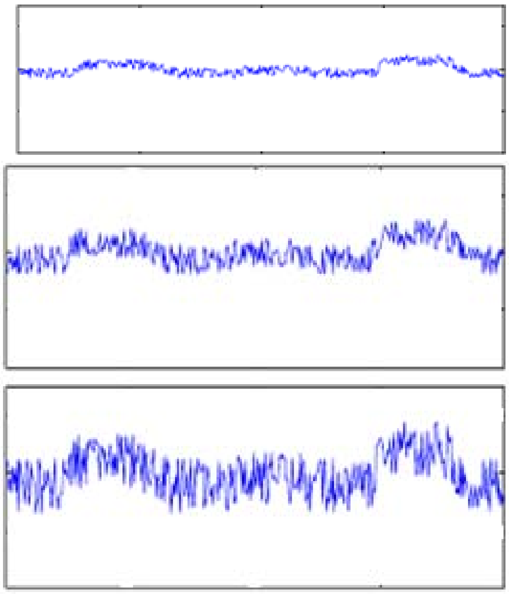

Figure 2(a) Block – I: Correlation among the samples and its delayed versions at lower frequency

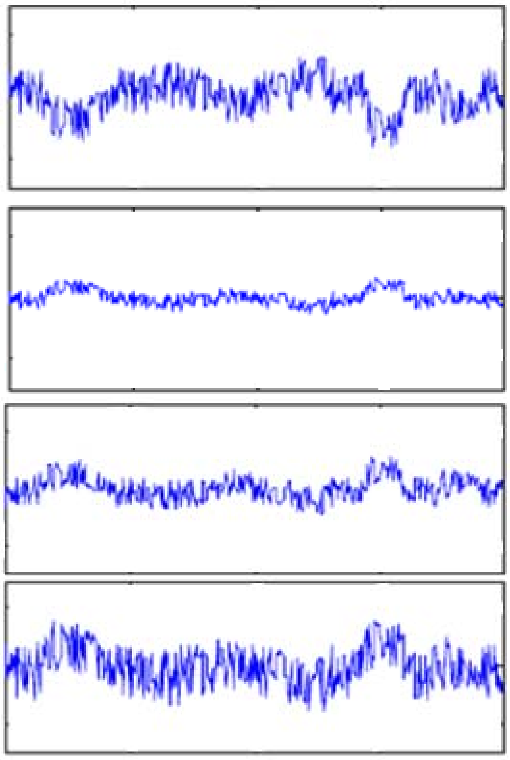

Figure 2(b) Block – I: Correlation among the samples and its delayed versions at higher frequency

2.2 Motion Estimation Filter (MEF)

The MEF is designed to process the output of block – I and perform lower and higher frequency human motion estimation. The main role of MEF is to separate the uncorrelated samples from the correlated ones and perform estimation of human motion as shown in Figure 3.

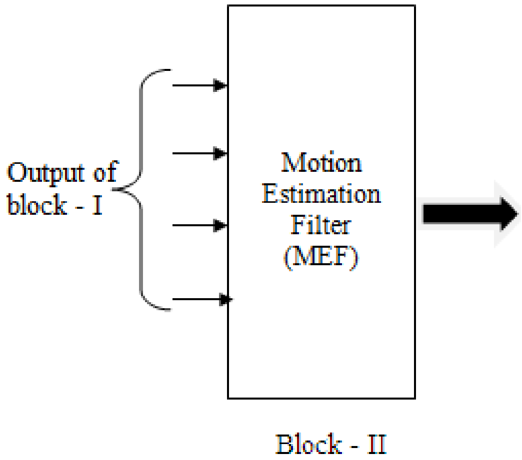

Figure 3 Block diagram of Motion Estimation Filter

The human motion estimation filter is processed in three stages and is shown in Figure 4.

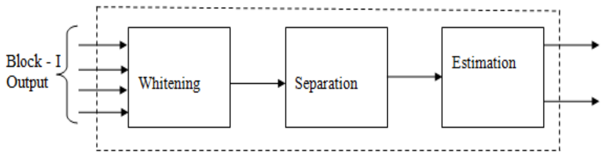

Figure 4 Stages of Motion Estimation Filter

Stage 1: Whitening: This stage normalizes the human motion video samples to unit variance.
Stage 2: Separation: After normalization, this stage separates the uncorrelated samples (noise) and the correlated samples (i.e. the human motion).
Stage 3: Estimation: Finally, using the trained weights, the motion estimation filter estimates the human motion video.

2.2.1 MEF Algorithm

The human motion estimation algorithm is designed to extract the mean value of the human motion picture and identify the correlation, eigenvalues in the diagonal elements of the human motion components and the correlation coefficients between the human motion picture samples. The MEF algorithm is described in the flowchart of Figure 5.

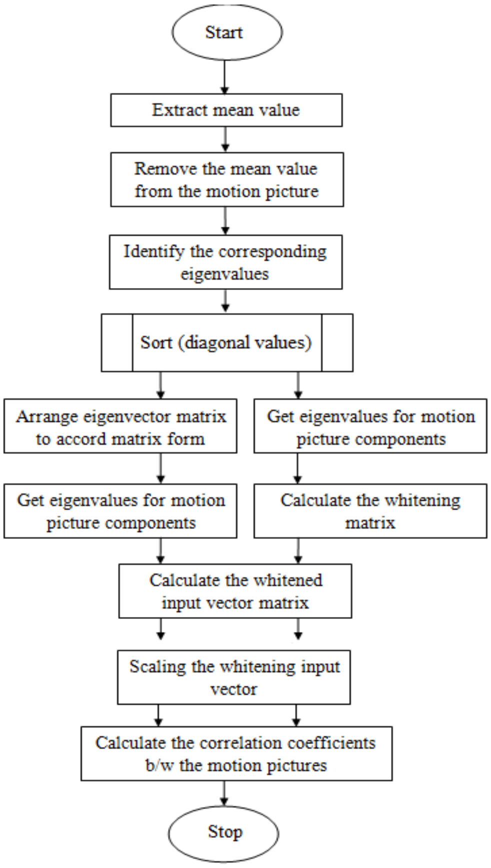

Figure 5 Flowchart of MEF

3. Phase Compensator integrated MEF

At higher frequencies, the MEF introduces an unintentional phase shift of 180° in the estimated human motion. To compensate for phase shift, the MEF block is modified with the decision and 180° phase shift module and is shown in Figure 6.

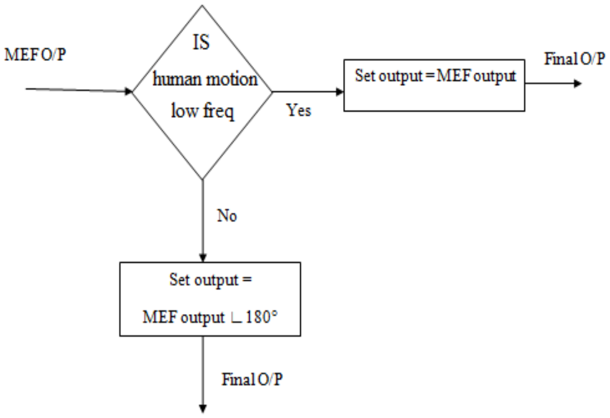

Figure 6 Phase compensator integrated MEF

4. Experimental study

The proposed MEF is studied for two situations namely; (i) Low Frequency Motion Estimation (LF_{MEF}) and (ii) High Frequency Motion Estimation (HF_{MEF}). In both the cases, the human motion in the video input is varied and studied. The performance of the proposed MEF is inferred by computing the auto correlation and cross correlation values between the original motion picture and the MEF output. The trained weights for the two cases are given in Table 1.

Table 1: Trained weights in low and high frequency of Motion Estimation

Frequency	Trained Weights
Low Frequency	$\begin{bmatrix} 0.948 & -0.3207 \\ 0.3206 & 0.9476 \end{bmatrix}$
High Frequency	$\begin{bmatrix} 0.9945 & 0.1114 \\ -.0.1114 & 0.9942 \end{bmatrix}$

Also, the mean square error is obtained. The plots are shown in Figure 7(a), 7(b) and 7(c) respectively.

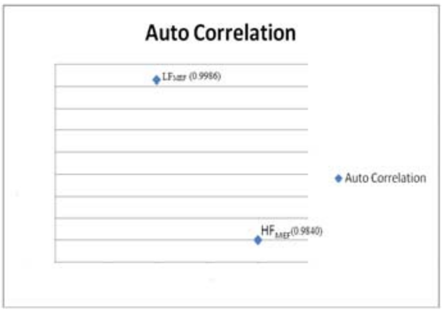

Figure 7(a) Auto Correaltion at LF_{MEF} and HF_{MEF}

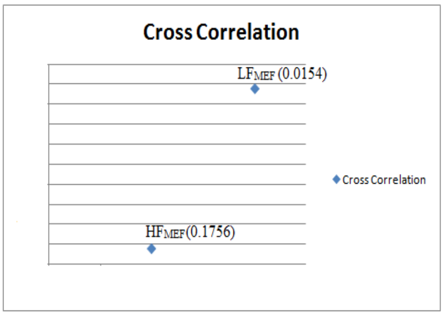

Figure 7(b) Cross Correaltion at LF_{MEF} and HF_{MEF}

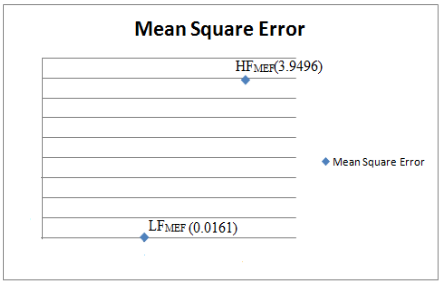

Figure 7(c) Mean Square Error at LF_{MEF} and HF_{MEF}

5. Results and Discussion

Case (i): Low Frequency MEF

In this section, the tracking of human motion and the estimated MEF output in polar coordinates is obtained and the corresponding coordinate plot of the human motion is shown in Figure 8(a) and Figure 8(b) respectively. It can be inferred from the plot that the MEF performs vector tracking effectively and is ideal for low frequency motion estimation.

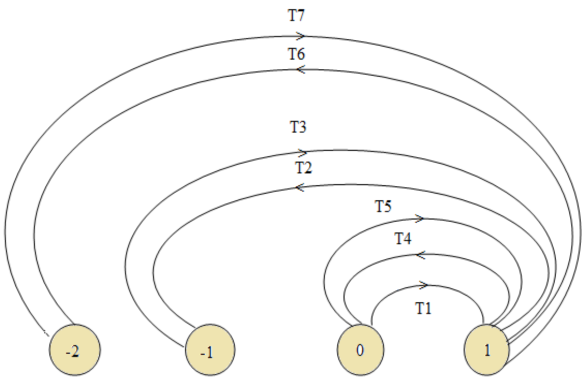

Figure 8(a) Original human motion at low frequency in polar coordinates

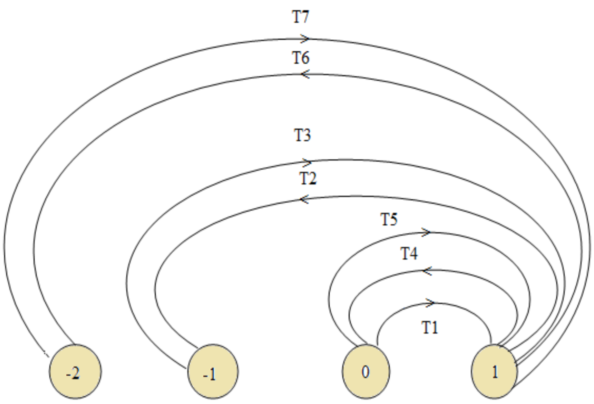

Figure 8(b) Estimated human motion at low frequency in polar coordinates

Case (ii): High Frequency MEF

In this section, the tracking of human motion and the estimated MEF output in polar coordinates is obtained and the corresponding coordinate plot of the human motion is shown in Figure 9(a) and Figure 9(b) respectively. It can be inferred from the plot that the MEF performs vector tracking less effectively and is constrained for high frequency motion estimation. However, using the phase compensator of Figure 6 this mismatch can be removed.

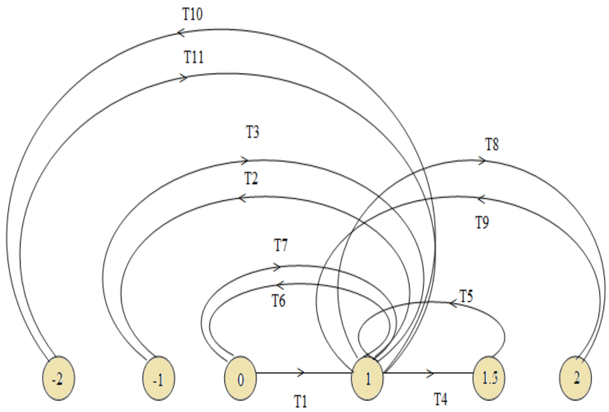

Figure 9(a) Original human motion at high frequency in polar coordinates

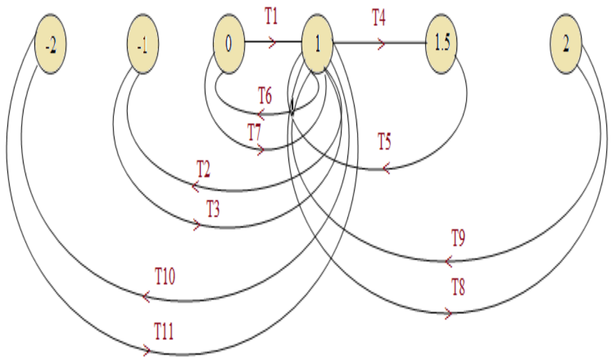

Figure 9(b) Estimated human motion at high frequency in polar coordinates

5.1 Inference from results

From the results it is inferred that the performances of MEF depends on the rate of change of human motion. At low frequency, the estimated output matches in both phase and magnitude, whereas at high frequency, an undesirable phase change is introduced. This is reflected in Figure 9(b) when compared with Figure 9(a).

6. Conclusion

In this work, an adaptive motion estimation filter is proposed for a human motion estimation using polar coordinate projection. The filter is designed to reconfigure itself and provide real-time noise cancellation. The result obtained is satisfactory and show the validity of the approach to adaptive noise separation and motion estimation. The designed MEF filter can track the true variations of the motion pictures with minimal mean square error. The architecture shall be implemented as a reconfigurable fabric in a pipelined fashion (improved speed).

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Author's Biography

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