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A METHOD FOR ENHANCING EYE MOVEMENTS DATA FROM EYE-TRACKING DEVICES

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Abstract. Eye movements play an important role in actual neuroscience and in the last twenty years, many eye-tracking devices have emerged with different methods and performance features. Generally, the highest quality ones with best performance in terms of accuracy and high framerates, are the most expensive apparatus and very often complicated to assembly. Also, they tend to work in fixed setups and it is hard to perform outdoor experiments, like driving a real car or walking long distances. The comfortable and cheaper ones are usually those having the poorest measuring characteristics, reaching maximum framerates below 250fps, yet with great advantages. These modern remote eye-tracking systems allow, in general, small head movements and the subject has not wear any kind of hardware. This feature is especially important when working with children or people with some kind of physical impairment. They are independent, small and one-piece hardware ready to plug into a mobile computer or laptop, making easy to set a large variety of experiments. In this work, we propose to use wavelet methods to improve real eye movements data, allowing the reconstruction of the signal at a higher resolution than the original one. Transformed data was upsampled and the new coefficients were obtained by interpolation using different techniques and looking for a minimum percentage error between the original and recovered signals. Then, treating the eyetracker data with low samplerate as a complete signal with *periodic missing parts or information* and inspired in a method for restoring very damaged images, we present an approach to adapt one of the the algorithms for images to 1D signals.

1 INTRODUCTION

Eye movement analysis using eye tracking allow us to evaluate attention, interest and arousal. This information of human behavior is relevant in a variety of fields such as Engineering, Medicine, Psychology, Gaming, Marketing, etc. It is also used for enhancing human computer interaction in motor impaired people by using the eyes for navigation and control. Besides, during the last twenty years, important results have been achieved in evaluation and early detection of neuropathological diseases (Fernández et al., 2015) or ths possibility of detecting early cognition impairment (see, for example, (Fernández et al., 2014b,a, 2016)).

According to the increasing rate of different applications of the register of eye movements it has become necessary to develop better and more precise devices. Also, many different techniques have appeared along the applications but some of them can be very uncomfortable, even invasives, for the subject to whom are applied. Nevertheless, a new broad variety of detection techniques are based on digital video analysis making the eye tracking devices very popular although very expensives. In order to have high performance and good accuracy, the video camera used in these devices need have a large framerate and the setup of the system requires very particular software specification and development. With the actual development of technology, it is possible to have high-quality cameras and fast enough computers to process video in real time for performing eye-tracking. Even small and independent hardware have been developed to achieve these tasks (*e.g.* Tobii eyeX, SMI Eye Tracking). These modern devices are good enough to make reliable measurements, but they still are a bit expensive.

With the posibility of having access to open source software (*e.g.* PyGaze, OpenCV) it is possible to have built in home and cheap eye-tracking systems, but although the results can be considered acceptable, they are poorly accurate for some applications. Using commercial webcams, it is possible to have good spatial accuracy (say 1°) in these devices but the framerate is only 30fps or 60fps in best case being hard to get faster home cameras that can perform live capure at a higher framerate. This has motivated us to apply a well known 2D technique applied in image processing to improve the resolution of the 1D eye tracking signal.

In this context, we have taken into account the problem of restoration of images when some information was lost since we believed that it could give as an insight to the problem of adding samples to a 1D signal for obtaining a signal with higher sample rate. In this sense, we propose to treat the lack of value at the added sample as the lack of information during the restoration process. Taking into account methods for fast image restoration based on wavelet analysis (for example, (Hsieh et al., 2009)), in this work we consider a signal measured with a low and non-constant samplerate as an image with missing blocks and regions. In this work we propose wo different approaches to this technique. The first one is to decompose first the signal using the discrete wavelet transform, upsample the signal corresponding each resolution and then try different interpolation techniques to assign the value to the missing coefficients mantaining the peaks and its width. The second one consists of first upsmaple the signal we want to enhance and then decompose both, the the original and upsampled signals, using the discrete wavelet transform. To give the value to the missing coefficients we applied a similar methodology to the one used (Hsieh et al., 2009) adapted to 1D signals. Finally, in both cases, we performed the inverse wavelet transform and obtained a signal that doubled the frame rate of the original one.

Figure 1: Eye movements during freely looking at an image. (Specht et al., 2017)

2 BACKGROUND

2.1 Register of eye movements

The participants were seated in front of the monitor at a distance of 60 cm. Head movements were minimized using a chin rest. The participants' eye movements were recorded with an Eye-Link 1000 Desktop Mount (SR Research) eyetracker, with a maximum sampling rate of 1000Hz and an eye position resolution of 20-s arc, being all recordings and calibration binocular. The participants' gaze was calibrated with a standard 13-point grid for both eyes. After validating the calibration, a fixation point appeared for 1 second at the center of the screen and then an image of *search for the differences* kind was shown for over 1 minute, as made in (Specht et al., 2017). The only intention for the experiment is to gather as many movements as posible in a short time.

In Figure 1 can be observed how the eyes movement pattern when freely looking at an image. The eye tracker register these movements and keep the position on both horizontal and vertical axes and the time duration of the gaze on each position for both eyes.

2.2 Discrete wavelet transform

Wavelets are a mathematical tool that allows a hierarchical decomposition of functions and its origins were different fields, such as signal processing and physics. Its theory has been developed during the last century and they have been implemented in a great number of applications, including signal and image processing and analysis. The traditional books (Daubechies, 1992; Mallat, 1998) are example of the many books where wavelet theory is carefully and fully developed. Form the signal point of view, wavelets can be seen as dilations and translations of a single function, called *mother wavelet*, being the Fourier transform the main tool for this construction.

Briefly, wavelets can be thought as basis functions used to represent signals which have the special feature of being well localized in both spatial and frecuency domains. This property can be thought as having a finite and adaptive sliding window in time domain that determines a sliding window in the frequency domain, which allows to select only a frecuency band. Another important feature of discrete wavelets is the *multiresolution analysis* (MRA). Basically, this analysis can be thought as an infinite sets of nested subspaces $\{V_j\}_{1\leq j<\infty}$ of $L^2(\mathbb{R})$ such that its union give the whole space $L^2(\mathbb{R})$.

The basis for each V_j is generated by translations and dilations of a single basic function $\varphi(t)$ called *scaling function*. The basis functions are then given by

$$\varphi_{j,k} = 2^{-j/2}\varphi\left(2^{-j}t - k\right), \quad j,k \in \mathbb{Z}. \tag{1}$$

For each one of the subspaces V_J can be obtained a complementary subspace W_j with a basis given by the dilation and translations of a single function $\psi(t)$ called *mother wavelet*. Then the basis functions for these subspaces are

$$\psi_{j,k} = 2^{-j/2}\psi\left(2^{-j}t - k\right), \quad j,k \in \mathbb{Z}. \tag{2}$$

Taking into account the definitions (1 and 2), the sliding window in the time domain is determined by the support of each one of these basis functions (Bultheel and Huybrechs, 2014).

The Discrete Wavelet Transform (DWT) can be seen as the projection of a given function $f \in L^2(\mathbb{R})$ onto the spaces W_j and gives one of the most practical application for representing functions in the spatial-frecuency domain. If $\langle\cdot,\cdot\rangle$ stands for the scalar product on $L^2(\mathbb{R})$ it is possible to say thet any function $f \in L^2(\mathbb{R})$ can be written as follows (see, for example, (Bultheel and Huybrechs, 2014)):

$$f(t) = \sum_k c_{j,k}\varphi_{j,k}(t) + \sum_{j=0}^{J} d_{j,k}\psi_{j,k}(t) \qquad j,k \in \mathbb{Z}. \tag{3}$$

being $c_{j,k} = \langle f, \varphi_{j,k}\rangle$, $d_{j,k} = \langle f, \psi_{j,k}\rangle$ the expansion coefficients.

The choice of the scaling function and the mother wavelet strongly depends on the application and could be several choices. Taking into account the shape of the signal corresponding to eye movements data, we have started by using the Haar functions.

3 MEHODOLOGIES FOR ENHANCING THE SIGNAL

3.1 Method using interpolation

Interpolation methods estimate the value at point that lies within the domain of a set of sample data points but where the real value is not known. There are many different interpolation methods but they all share the characteristic that the interpolating function passes through the data points. This is an important distinction between interpolation and curve fitting since in curve fitting methods, the function does not necessarily pass through the sample data points.

The computation of the new value is generally based on the data points in the neighborhood of the missing point. In this work we have considered three different interpolation methods: nearest neighbor interpolation, cubic interpolation and spline interolation. The nearest neighbor interpolation sets the value of an interpolated point to the value of the nearest existing data point. The cubic interpolation method perform piecewise cubic Hermite interpolation of the values at neighboring grid points and this methods preserve monotonicity and the shape of the data since the resulting interpolated function has continuous derivative. Finally, the cubic spline interpolation fits a different cubic function between each pair of existing data points, and uses the spline function to perform cubic spline interpolation at the data points.

The interpolation methods are used as follows. First, the signal we want to enhance is decomposed in three levels of resolutions using the DWT. Then, each resolution level is upsampled by 2 and the missing value at each of this new samples are considered as the damaged part of the signal. Using different interpolation methods we established the value for the coefficients corresponding to each of these new points, taking care not only that every peak of the decomposed signal for each resolution fell in the correct place (twice the original) but also kept its peak width. Also, we applied hard thresholding to the wavelet coefficients. Finally, we applied the Inverse Discrete Wavelet Transform (IDWT) to recover the signal, obtaining a signal that doubled the number of the original points corresponding to the same time measuring lapse. That is, we obtained an enhanced signal like if we had it sampled at a higher framerate.

3.2 Signal restoration method

This methodology is based on the 2D method described in (Hsieh et al., 2009). In that work, the idea is to repair the damaged block of the image using its whole information on each level of the wavelet decomposition. The algorithm takes into account the four possible directions of the image (horizontal, vertical, and both diagonals) and, taking into account the value of the wavelet coefficients of the neighbours in each direction, replaces the missing coefficients corresponding to that block with the value that is closest to each one of them. This replacement is not direct but the value of the coefficients are adjusted using a criterion of best adjustemnt to connect with the neighborhood blocks. As we have a 1D signal, the searching direction is only the horizontal one.

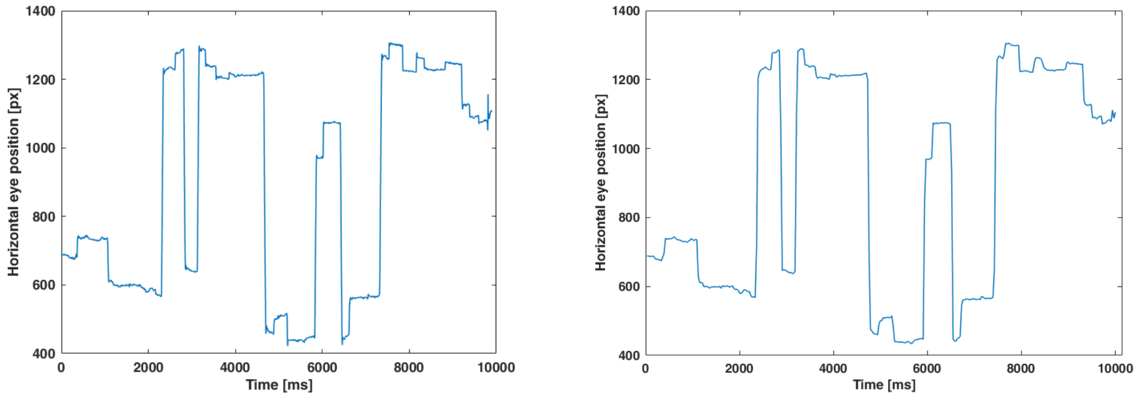
First af all we perform the DWT on the original signal (f_0) using three levels of decomposition (fw_0). Then, a zero value is added every two samples, obtaining a transformed signal fw_{up} that has doubled its sample rate. Let us note $x_i, i = 1, \dots N$ the added samples in each resolution. If we define a vector $\vec{v}$ with the value of the coefficients corresponding to the right and left neighbours to each added sample and we calculate the distance of $\vec{v}$ to a sliding window vector $\vec{s}$ containing pairs of values within a fixed range of 100 points over the non-upsampled transformed signal fw_0, then we find the minimum distance and reassign the value of the missing coefficients x_n with the linear interpolated value between the components of $\vec{s}_{min}$ calculated in $n/2$.

$$\begin{aligned}
&\vec{v}_n = [fw_{up}(x_{n-1}), fw_{up}(x_{n+1})],\\
&\vec{s}_{n,j} = [fw_0(x_{((n-1)/2)+j}), fw_0(x_{((n+1)/2)+j})],\\
&d_j = ||\vec{v}_n - \vec{s}_{n,j}||,\\
&MSE_n = \min_{-100\leq j\leq 100}(d_j),
\end{aligned} \tag{4}$$

The minimum MSE_{n_0} is achieved for some value of n_0. As said, for that value, we give to the new coefficient $fw_(x_{n_0})$ the value on the middle point $n_0/2$ of the linear interpolation between the points $\left(x_{((n_0-1)/2)}, fw_0(x_{((n_0-1)/2)})\right), \left(x_{((n_0+1)/2)}, fw_0(x_{((n_0+1)/2)})\right)$.

4 METHODOLOGY AND RESULTS

For the analysis we worked with registers of real eye movements data gathered from a SR-Research EyeLink 1000 eye-tracker. The sample rate of the original signal is 500Hz (see Figure (2)(a)) and from this data we considered 10 seconds corresponding to the horizontal position of the left eye during free viewing of an image of a natural landscape corresponding to an anonymous subject. In order to simulate the same signal but sampled at a lower framerate, we downsampled the original one with a step of 30 points, obtaining a similar signal but with less resolution (330 points) and framerate speed of 33fps (see Figure (2)(b)).



(a) Original data. Data points: 5000 (500fps) (b) Downsampled data. Data points: 330 ($\sim$ 33fps)

Figure 2: Data used for testing the method: horizontal left eye position vs. time

To compare the enhanced signal with the original one straightforwardly, we worked with this resampled signal. We first performed the DWT to the signal using the Haar wavelet, with three levels of decomposition and we also tested the method using Daubechies3 wavelet. In what follows, we present the results obtained using the interpolation methods describead in Subsection 3.1 and the signal restoration method described in Subsection 3.2.

4.1 Using cubic-splines interpolation

For each resolution level, we used cubic-splines interpolation for establishing the value of each coefficient on the new points. In Figure (3) we present the results of applying this method using the Haar wavelets and in Figure (4) the results of using the Daubechies3 ones.
The restored signal with this method for both wavelet transforms has very good matching with the high framerate signal (red colored line), with a mean percent error in the difference of both of 0.69% for the Haar wavelet case and 0.42% for Daubechies3.

4.2 Using nearest neighbor interpolation

Now we applied the nearest neighbor method for finding the value of each coefficient on the new points. Results using the Haar and Daubechies3 wavelets are shown in Figure (5) and Figure (6), respectively.
In this case, mean percent error in difference is greater for both types of wavelet transform, giving 1.32% for Haar wavelet and 0.58% for Daubechies3. There is a poor matching of the restored signal and the high framerate signal using this interpolation method. This is probably due to the fact that in this mehod high frecuency noise affects the interpolated values used to assign the values to the new upsampled points.

4.3 Using cubic interpolation

Next, in Figure (7) and Figure (8) we present the results obtained applying cubic interpolation method for reasigning new values to the added points using the Haar and Daubechies3

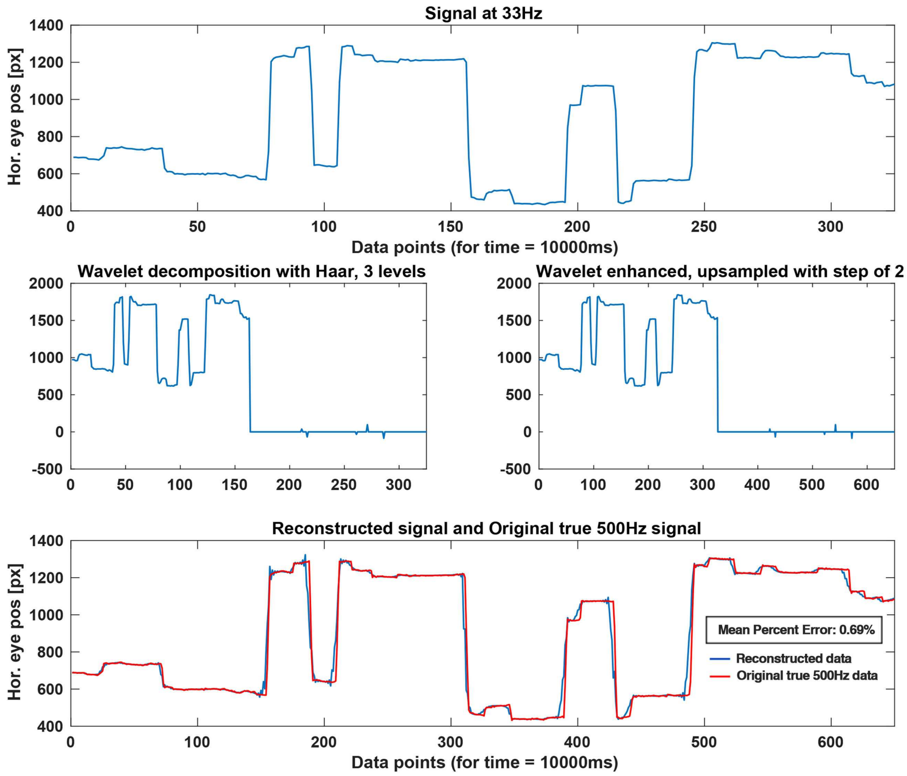


Figure 3: Results using Haar wavelet transform and cubic-splines interpolation.

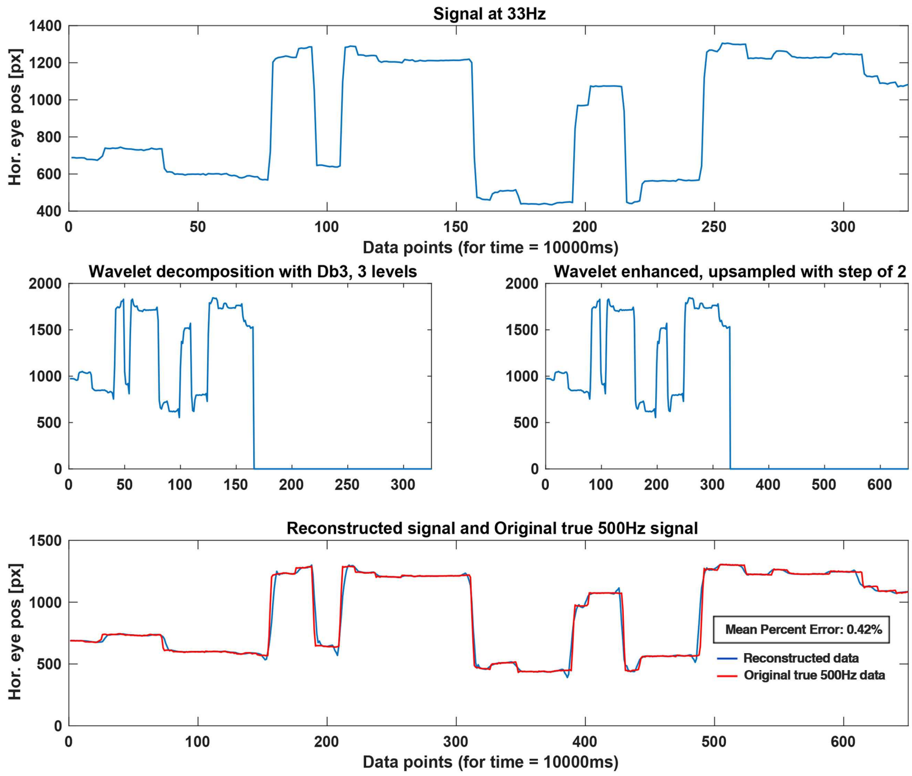


Figure 4: Results using Daubechies3 wavelet transform and cubic-splines interpolation.

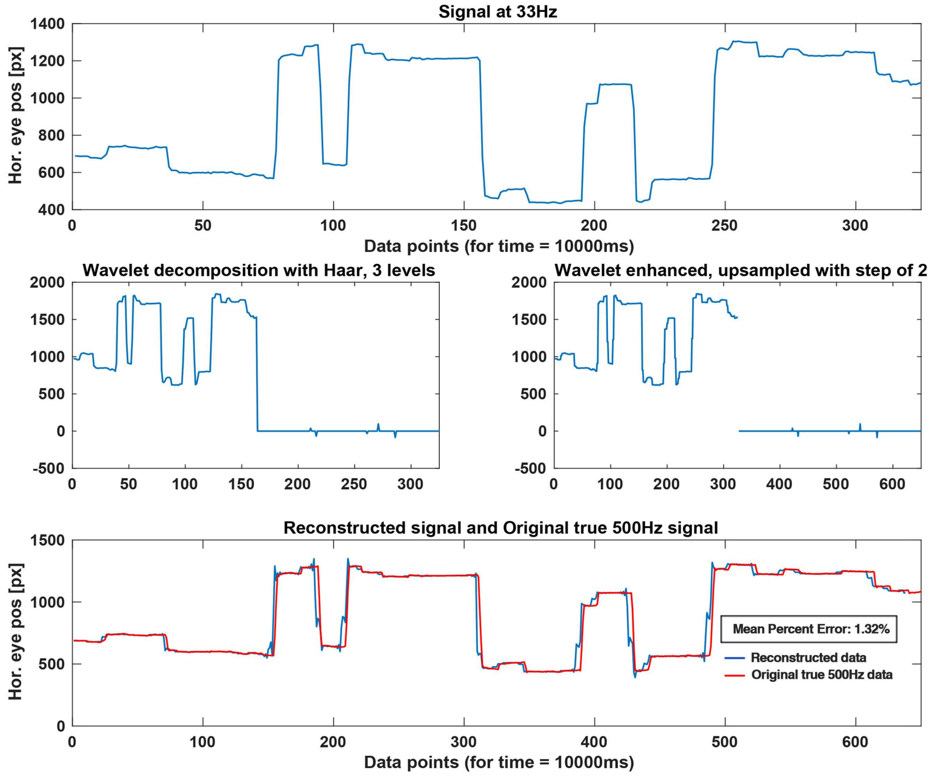


Figure 5: Results using Haar wavelet transform and nearest neighbor interpolation.

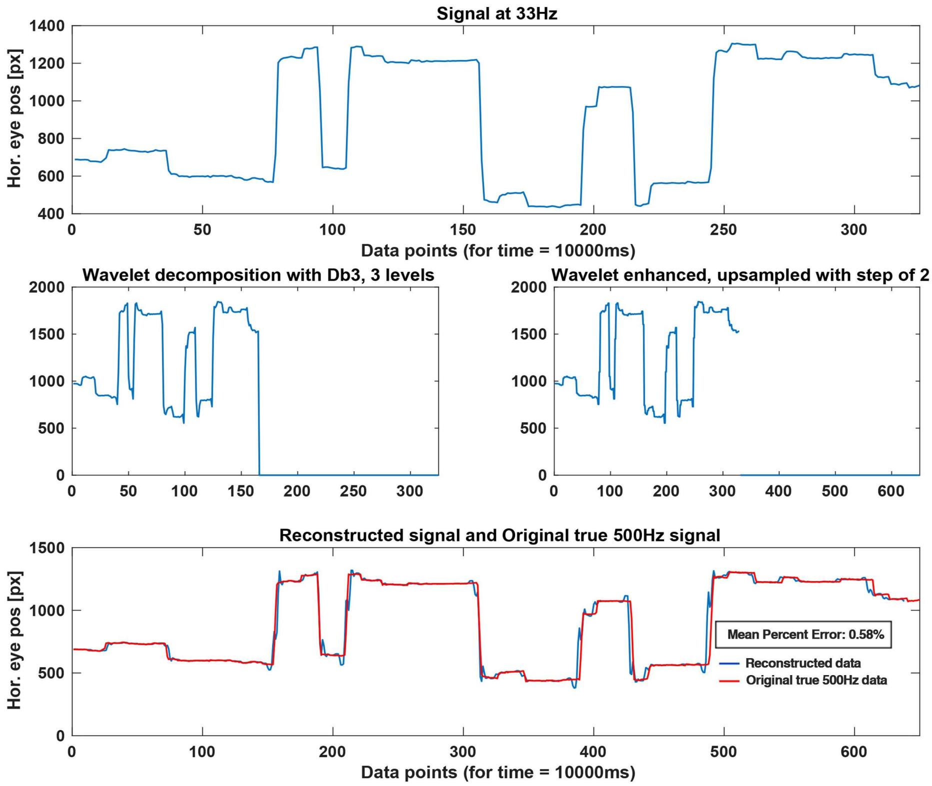


Figure 6: Results using Daubechies3 wavelet transform and nearest neighbor interpolation.

wavelets, respectively.
Ther is more accurate matching for the restored and high framerate signals using this interpolation methodology, with mean percent error in difference of 0.73% for Haar wavelet and only 0.19% for Daubechies3.

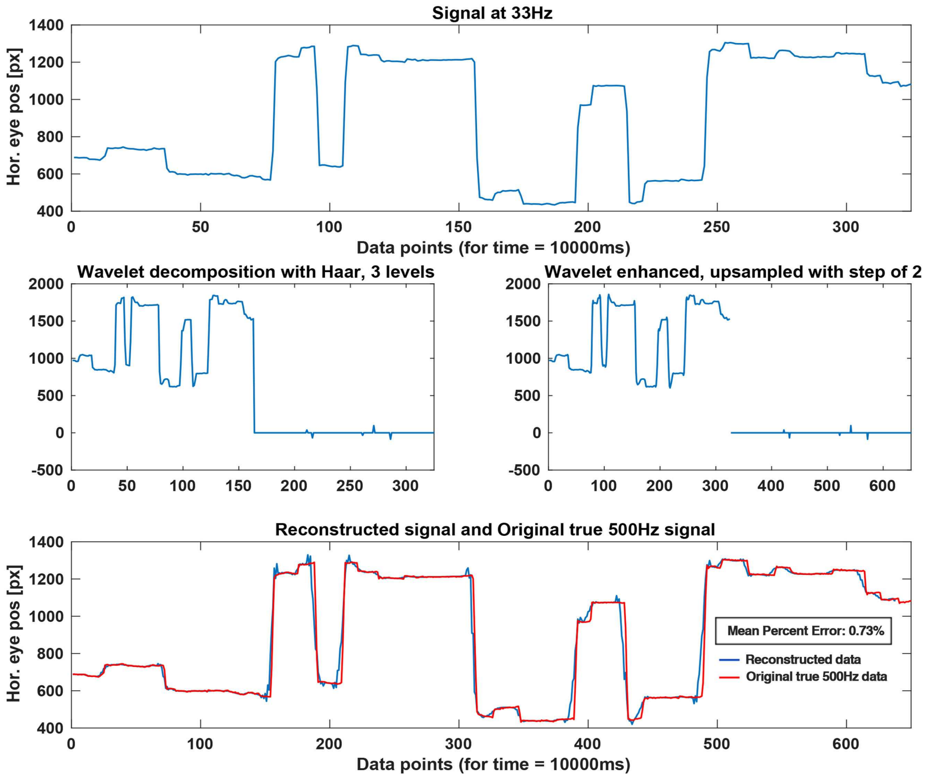


Figure 7: Results using Haar wavelet transform and cubic interpolation.

4.4 Using restoration method

In what follows we present the results of implementing signal restoration presented in Section 3.2. Figure (9) corresponds to results using Haar wavelet transform and Figure (10) corresponds to results using Daubechies3 wavelet transform.
Results are not so accurate for this adapted method, giving the largest mean percentage corresponding to recovered and high framerate signals. This are 2.6% and 1.5% for the Haar and Daubechies3 wavelets, respectively. This method has proved to be highly efficient and reliable for image restoration in 2D, nevertheless it shows some difficulties when using for 1D signals. A more exhaustive analysis on the adaptation might be investigated in order to get better results.

5 CONCLUSION

In this work many methods for enhance low framerate eye movements recordings were tested in order to achieve to a practical way for at least duplicate original signal framerate without losing presition. Although a more detailed analysis is required for tuning the methods, the results presented here are really encouraging. Signal restoration method, adapted from its 2D version, proved to be not accurate enough as expected from the goodt results seen in image restoration

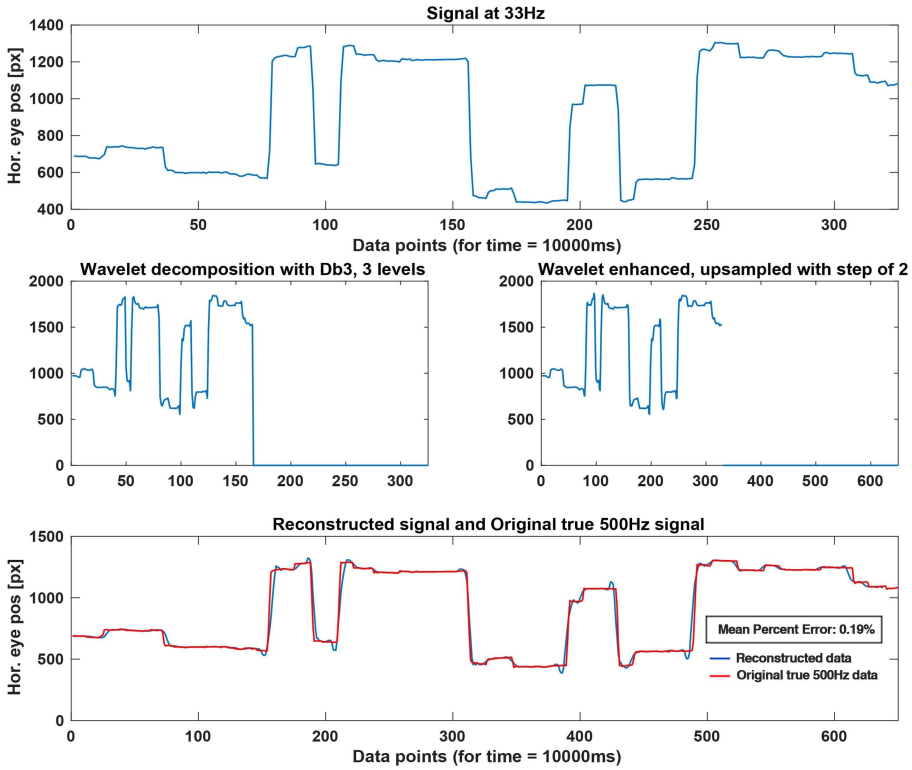


Figure 8: Results using Daubechies3 wavelet transform and cubic interpolation.

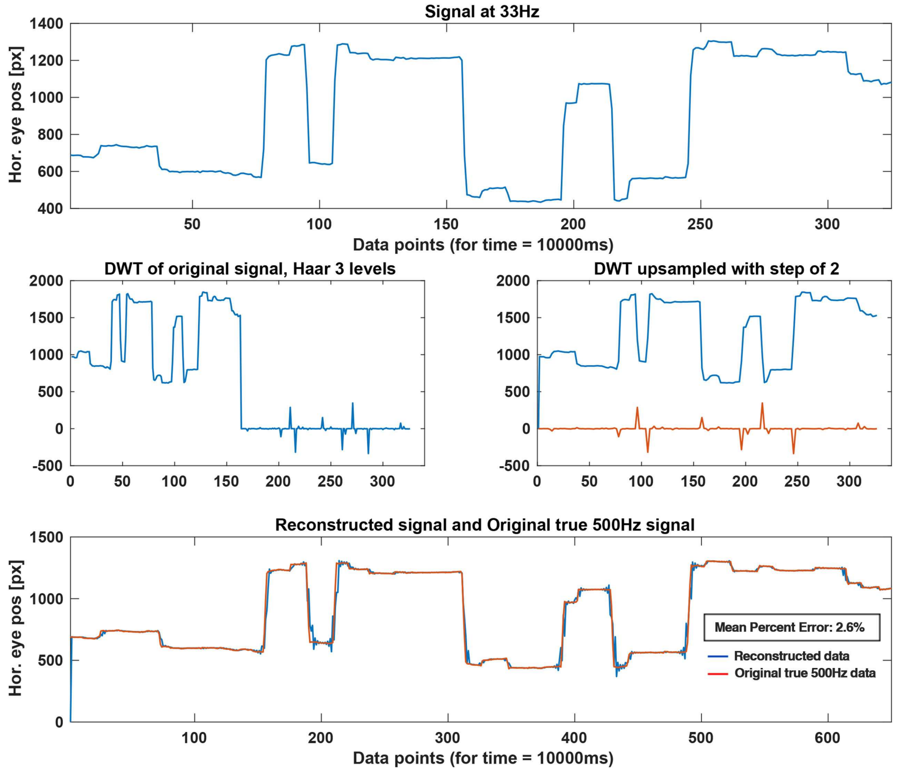


Figure 9: Results using Haar wavelet transform and restoration method.

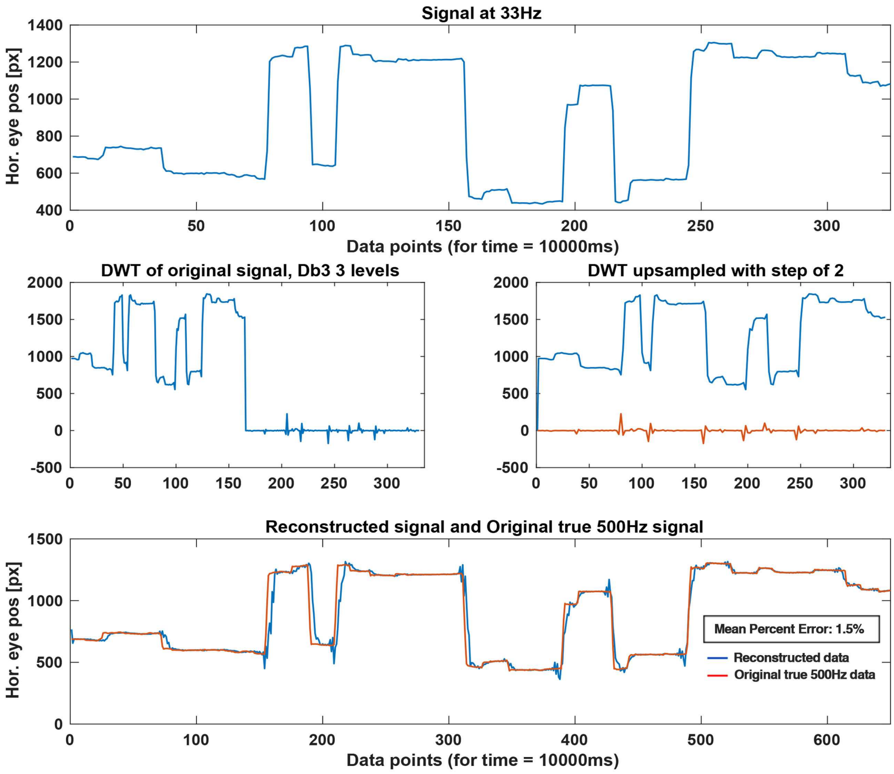


Figure 10: Results using Daubechies3 wavelet transform and restoration method.

techniques. On the other hand, interpolation method for assigning added values during upsampling of the wavelet transformed signals showed better behavior with lower mean percentage error between the enhanced signal and the high framerate ones. The best result was obtained using Daubechies3 wavelet transform and interpolating the added zero values from the upsampling with a cubic function, giving a mean percentage error for the difference in the recovered and high framerate signals of only 0.19%.

Many of the impresitions of the methods may be due to high frecuency noise, that gets more evident in nearest neighbors and difficult accurate value replacement for the upsampled points. An extended neighbor solution for polynomial interpolation may be developed for obtaining higher confidence results. Moreover, in future work a machine learning method will be tested, like training a neural network with coefficients of real high framerate signals from eye movements recordings and then use this information for adjusting the added values during upsampling of wavelet transformed signals of poor sampled measurements.

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