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COMPARISON OF TIME WARPING ALGORITHMS FOR RAIL VEHICLE VELOCITY ESTIMATION IN LOW SPEED SCENARIOS

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Abstract

Precise measurement of rail vehicle velocities is an essential prerequisite for the implementation of modern train control systems and the improvement of transportation capacity and logistics. Novel eddy current sensor systems make it possible to estimate velocity by using cross-correlation techniques, which show a decline in precision in areas of high accelerations. This is due to signal distortions within the correlation interval. We propose to overcome these problems by employing algorithms from the field of dynamic programming. In this paper we evaluate the application of correlation optimized warping, an enhanced version of dynamic time warping algorithms, and compare it with the classical algorithm for estimating rail vehicle velocities in areas of high accelerations and decelerations.

Keywords: velocity estimation, cross-correlation, dynamic programming, eddy current sensors.

1. Introduction

Reliable and precise measurement of the velocity of a rail vehicle is crucial for the application of modern train disposition systems aimed at increasing the efficiency and thus the amount of goods and persons transported on already existing tracks [1]. Current systems are built upon standard velocity sensors like *Global Navigation Satellite System* (GNSS) receivers or radar systems that face problems when dealing with heavy environment conditions or shadowed areas like rail stations or dense forests [2]. In contrast, an eddy current sensor system enables non-contact measurement of speed and distance of rail vehicles by measuring the magnetic inhomogeneities along the track and utilizes the cross-correlation technique to determine the time shift between two sensor heads mounted within the housing at a set distance from each other [3]. The sensor system works effectively, especially at higher velocities. Nonetheless, this type of sensor encounters difficulties in phases of high deceleration and acceleration as well as in passages with very low speed manoeuvres, *e.g.* when passing over turnouts in railway stations. This paper presents a signal processing approach, based on the so-called warping algorithms, a specific application of the dynamic programming [4] so that these problems at lower velocities can be overcome.

Two types of algorithms are examined: the classical *dynamic time warping* (DTW) algorithm [5] and an adapted variant, the so-called *correlation optimized warping* (COW) algorithm [6]. They are compared with the classical cross-correlation approach, based on a closed-loop correlator [7–9]. Warping algorithms are commonly used for the task of sequence classification, where they are capable of distorting one signal sequence by stretching it so that it is comparable to a class template. This paper makes use of this signal straining, as it is directly proportional to the difference of the two signals determined by cross-correlation. Fig. 1 shows an overview

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of the system. The $s_1(t)$ and $s_2(t)$ are the output signals from the two sequentially placed *Eddy Current Sensors* (ECSs). As long as the rail vehicle moves below a certain velocity, *i.e.* when starting or coming to a halt, the speed is determined by means of the two warping algorithms. A velocity threshold determines when the common closed loop correlator or the warping algorithms should be used for velocity estimation. When driving faster, which is the case on open tracks, a *closed loop correlator* (CLC) is employed for estimation.

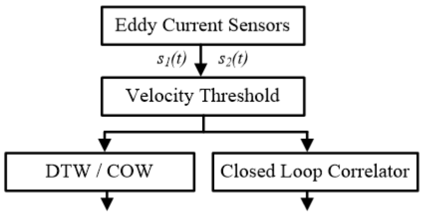

Fig. 1. A system overview.

2. Eddy Current Sensor System

2.1. Working principle and sensor system

ECSs are commonly used to detect inhomogeneity in the magnetic resistance of conductive materials [10]. This basic approach has been further developed and adapted for applications on railway vehicles, including speed measurement and pattern recognition tasks [11]. The ECS system consists of two identical sensor devices, each built up with a transmitter coil and two pickup coils. Both sensors are sequentially placed within a housing mounted on the train bogie approximately 10 cm above the railhead. Fig. 2a demonstrates the principle of a single device of the ECS: The transmitter coil E excites a magnetic field H_E that induces eddy currents in metallic materials like the rail. The eddy currents induce an antipode magnetic field H_{EC}, that generates $u_{P1}(t)$ and $u_{P2}(t)$ voltages within the $P1$ and $P2$ pick-up coils, respectively. By interconnecting them differentially, the output signal $s(t) = u_{P1}(t) - u_{P2}(t)$ is a measure of rail inhomogeneities. These result mainly from rail clamps, turnouts and other irregularities, *e.g.* cracks or signal cables (see [3]).

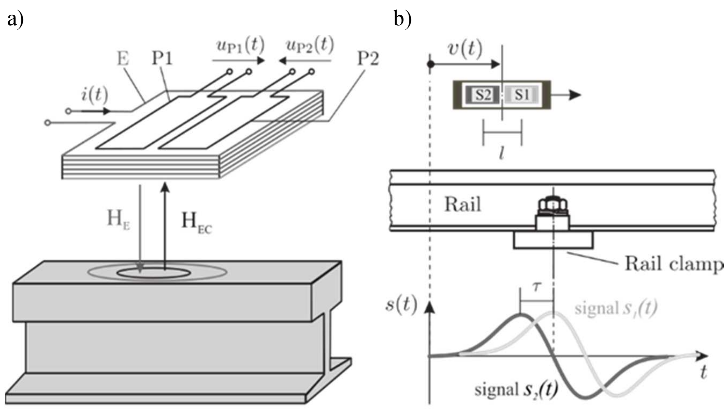

Fig. 2. A single ECS S1 (a); an example of signals in the ECS system (two sensors): $s_1(t)$ and $s_2(t)$, when crossing a rail clamp (b).

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The overall signal has a high *signal-to-noise ratio* (SNR), given that pre-processing low pass filters are installed in the sensor hardware.

2.2. Correlation based velocity estimation

The eddy current sensor system generates two signals: $s_1(t)$ and $s_2(t)$, each measured by the sensor heads $S1$ and $S2$, as shown in Fig. 2b and described in the previous section. If the rail vehicle is moving with constant velocity, the resulting signals are actually a low pass filtered sinusoidal of constant frequency and phase shift. This is due to the fact that the equidistance positioned rail clamps induce the main signal part. It is sufficient to know the coil distance l and time shift T to estimate the current velocity with:

$$\mathrm{v} = l/T. \tag{1}$$

The system setup for velocity estimation is shown in Fig. .

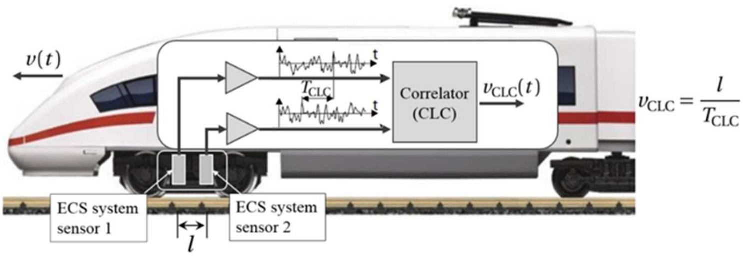

Fig. 3. The system setup for correlation-based velocity measurement.

The time shift within interval T_f is hereby determined with the *cross-correlation function* (CCF) $R_{s_1s_2}(\tau)$ defined as:

$$R_{s_1s_2}(\tau) = \lim_{T_f \to \infty} \frac{1}{T_f} \int_0^{T_f} s_1(t-\tau)\, s_2(t)dt\,. \tag{2}$$

The CCF has its main maximum at point $\tau = T_{\max}$, , $T_{\max} = \arg\max_{\tau}\{R_{s_1s_2}(\tau)\}$, where the signals are most similar to each other. The main idea now is to determine the time shift T on the basis of this maximum. Since the signals resulting from driving over rail clamps correspond to periodic signals, the CCF is also a periodic function [12]. Thus, it is more complicated to determine τ, as the maximum and its side maxima are indistinguishable in ideal circumstances. To prevent leaping between several maxima, the ECS uses a *Closed-Loop-Correlator* (CLC) that contains a model time-shift to track the peak of the CCF.

CLC is suitable for rail vehicle velocity measurement because of its good dynamic properties, its low statistical error and large measuring range [3]. The hardware implementation is based on the polarity correlation function:

$$R_{12}(\tau) = E\{\mathrm{sgn}[s_1(t)]\,\mathrm{sgn}[s_2(t-\tau)]\}. \tag{3}$$

This enables calculation based solely on the algebraic signs of the signal and significantly reduces the hardware implementation and computational effort.

The corresponding time-shift T_{CLC} of the polarity correlation function lies at its maximum, which is found by optimization with a gradient descent method. This optimization is implemented with the Newton-Raphson algorithm, an iterative method with fast convergence

[13]. The resulting block diagram of the CLC is shown in Fig. 4. Here $g_P(t,\tau)$ and $g_M(t,\tau)$ are the pulse responses of the system and of the model; sgn[...] is the signum function; $e(t)$ – the error and τ – the model run-time.

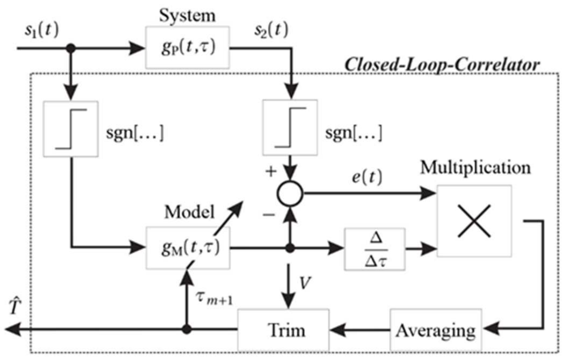

Fig. 4. The working principle of the described CLC. It is created as a signum correlator, optimized with an iterative Newton-Raphson scheme.

3. Velocity estimation with time warping algorithms

The above-mentioned approaches base on the assumption of a stationary stochastic process, which is true for a constant velocity within the cross-correlation interval. Although this assumption is correct in most situations, it is heavily violated in low-speed manoeuvres, where large changes in the relative velocity may occur. Unfortunately, this is the case in safety-relevant areas, *e.g.* within stations, where there are many turnouts and they additionally disturb the signals. The need for reliable distance estimation in localization scenarios makes it necessary to use velocity estimation, which could cope with these situations. Therefore, we propose to employ *time warping*, a dynamic programming scheme commonly used in machine learning and speech processing.

One of the presented methods, called *dynamic time warping* (DTW), was invented in the late 70 s initially either for aligning digitized samples of words pronounced by different speakers for recognition purposes [14] or for the alignment of biological sequences [15]. In recent years, a further development of this method, *correlation optimized warping* (COW), was proposed for the alignment of chromatographic profiles and spectra [16–18]. It was first suggested in 1998 as a way to correct chromatograms for shifts in the time axis prior to multivariate modelling and was based on incorporation of a cross-correlation correction step.

3.1. Dynamic Time Warping

Dynamic Time Warping (DTW) is commonly used for comparing data sequences, time series or classification samples. Certain test samples are compared with a reference sample by stretching the signal by duplicating distinctive data points. As a measure of quality, a cost function, *e.g.* the sum or squared sum, is minimized in an optimal way. Its efficient implementation by means of dynamic programming makes it widely used in machine learning applications, *e.g.* optical character recognition [19] or speech recognition as well as in robotics [20] and medical applications [21].

In this paper, we propose using DTW to determine the rail vehicle velocity by finding the time shift between the two sensor heads as a distortion necessary to realign the two sample

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signals. To clarify the basic idea of optimality by minimizing the cost function between the signals, a short description of DTW is given below.

The distance D between two signals $s_1(t)$ and $s_2(t)$ is defined by (4). As a cost function, the simple absolute distance is chosen:

$$D(s_1(t_i), s_2(t_j)) = \sum_{i=j=1}^{n} \left|(s_1(t_i) - s_2(t_j))\right| = \sum_{i=j=1}^{n} d[i, j]. \tag{4}$$

A constant time lag or non-stationarities in frequency and phase lead to large distances although the signals could be quite similar. The DTW algorithm eliminates this difference as it enables to keep a given data sample for several steps, *i.e.* stretching the signal to be compared, until the distance between the signals is minimized. An illustrative, quantitative example is shown in Fig. 5. It shows the two signals and the resulting path chosen to minimize the cost function in a so-called distance matrix. To achieve the minimization in an optimal sense, a so-called cost path W is introduced, which is defined as a series of indexed pairs:

$$\begin{aligned} W &= (w_1, w_2, \ldots w_K) \quad \text{with} \quad n \le K \le 2n-1, \\ w_k &= [i_k; j_k] \qquad\qquad 1 \le i_k; j_k \le n. \end{aligned} \tag{5}$$

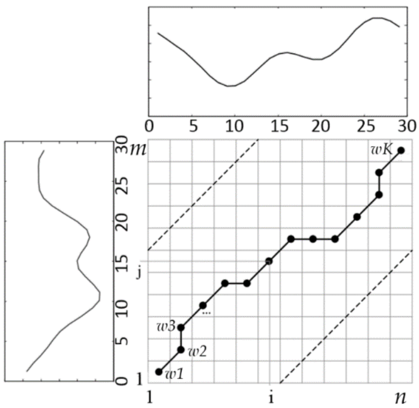

Fig. 5. A simulated cost path when warping a signal (image taken from [22]).

Thus, as shown in the Fig. 5, the individual sample points are reused to stretch the signal:

$$\begin{matrix} s_1(t_1) & s_1(t_2) & s_1(t_3) & s_1(t_4)\ldots, \\ s_2(t_1) & s_2(t_1) & s_2(t_2) & s_2(t_3)\ldots, \end{matrix} \tag{6}$$

which results in the corresponding path:

$$W = ([1;1],[2;2],[3;2],[4;3]\ldots). \tag{7}$$

To find the path W_{opt} with the lowest costs the optimization problem is formulated as follows:

$$D = \min_W \sum_{[i_k, j_k] \in W} d[i_k, j_k] = \sum_{[i_k, j_k] \in W_{opt}} d[i_k, j_k]. \tag{8}$$

Since not all possible cost paths are useful for the purpose of velocity estimation and in order to prevent singular solutions, the following constraints are introduced:

– Boundary conditions: $w_1 = [1;1], w_k = [n;n]$. This ensures that the start and end points of both signals are identical;

– Continuity:
given $w_{k-1} = [i_{k-1}; j_{k-1}]$ and $w_k = [i_k; j_k] \Rightarrow i_k - i_{k-1} \le 1$ and $j_k - j_{k-1} \le 1$. This constraint ensures that only adjacent cells can be reached in the path.
– Monotonicity:
given $w_{k-1} = [i_{k-1}; j_{k-1}]$ and $w_k = [i_k; j_k] \Rightarrow i_k - i_{k-1} \ge 0$ and $j_k - j_{k-1} \ge 0$. This last constraint forces monotonic spacing of the points regarding the time.

Direct solving the optimization problem according to (8) is not feasible because of the exponential computational complexity $O(n^n)$.

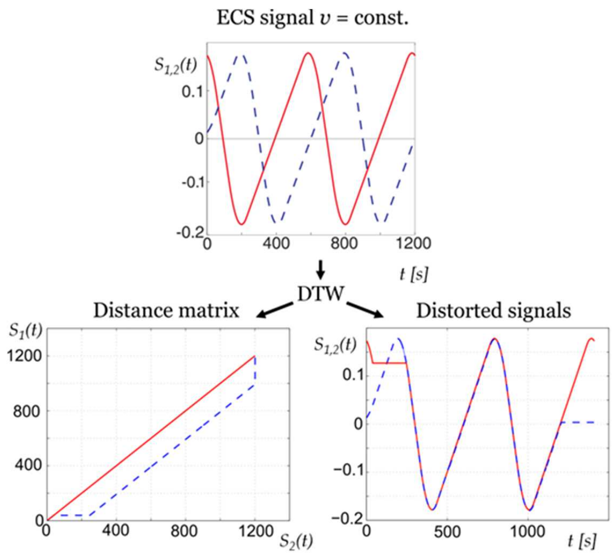

Fig. 6. The simulated result of DTW. The picture above shows ECS signals at a constant speed, where $s_1(t)$ is represented by a solid line and $s_2(t)$ by a dashed line. The corresponding distance matrix is shown below on the left, emphasizing the constant signal offset.
The warped signal is shown below on the right.

Instead, a cost matrix that contains all accumulated costs along all possible paths up to the concerned cell is created. By starting at the cell with the lowest final cost, the minimal cost path is found recursively, which reduces the computational effort to $O(n^2)$. The chosen path is optimal in the sense of Bellman [4] and is closely related to the well-known Viterbi algorithm. The result of applying the algorithm on idealized ECS signals is shown in Fig. 6. One can see from the corresponding distance matrix that the algorithm aligns the signals by eliminating the constant phase shift right at the beginning.

3.2. Correlation Optimized Time Warping (COW)

COW was first described as an adaptation of DTW in the field of gas chromatography [6]. In contrast to DTW, COW tries to adjust the two signals piecewise. Instead of the distance measure of (4), the signal similarity is based on a cross-correlation within the signals. To do this, the reference and target signals are divided into segments of m length, each of which can be either stretched or compressed. Due to this stretching, the segments must be shifted by a certain distance x_i which must satisfy the following condition:

$$x_i \pm u_i; [u_i \in (-t, t)]. \tag{9}$$

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After shifting the segments with a so-called slack t the stretched signal is compared with the reference signal by adapting the new segment size from $m + t$ or $m - t$ to the reference signal size and this is done by means of a linear interpolation. Afterwards, the signal similarity can be determined by a cross-correlation. The possible segment shifting by the slack and the subsequent comparison of the signals is not computationally feasible even for a small amount of segments and a small shifting slack. Therefore, the problem is solved again using a recursive approach based on optimal sub-solutions. The derivation of the final algorithm is outside the scope of this contribution and is described in detail in [6] and [18].

4. Simulation

4.1. Simulation framework

A simulation was done to verify the possibility of determining the shift of EDS signals with these warping algorithms. Therefore, several velocity profiles were simulated assuming a sleeper distance of 600 mm, a sensor distance of 208 mm and a sensor sampling rate of 1 kHz. Accelerations were restricted to a maximum of 3 m/s^2 which is the maximum achievable breaking power of typical rail vehicles. Afterwards, Additive White Gaussian Noise was added to simulate real-world disturbances. The sequences were chosen to have a length of 1–2 seconds which corresponds to the common correlator length. Simulated velocity profiles and their respective noise-free signals are shown in Fig. 7.

4.2. Simulation results

Given the simulated signals and velocity profiles, all examined algorithms, DTW, COW and the classical cross-correlation were tested with three scenarios: noisy signals at a constant velocity, noise-free signals with accelerations and noisy signals with accelerations.

Cross-Correlation

The results for the cross-correlation showed the expected behaviour. Noise-free signals at a constant velocity are reliably processed and white noise does not reduce the quality considerably. The simulated result for CCF with a distinctive peak (due to finite sample lengths) is shown in Fig. 8a. The case is different for a simulated starting scenario, shown in Fig. 8b. For the simulated acceleration of 2 m/s^2 one would expect an end velocity of 3 m/s, yet the correlation estimates an average velocity of 1.4 m/s within the interval. A decreasing correlation interval is not a viable solution because at least two rail clamp signals are needed to have a reliable estimate.

Classical DTW

The results of DTW for constant velocities have already been shown in Fig. 6. The degradation in the signal quality by *Additive White Noise* is not negligible. Fig. 9 shows the results for the constant acceleration scenario. The velocity estimate quality degrades rapidly and that leads to large jumps and false values.

COW

The results obtained by applying the COW algorithm on simulated and noise-free signals with a constant acceleration are shown in Fig. 10. The vector lengths indicate the amount by which the segments must be shifted to be matched. They are directly proportional to the corresponding velocity. Different lengths inside an interval indicate either acceleration or braking manoeuvres.

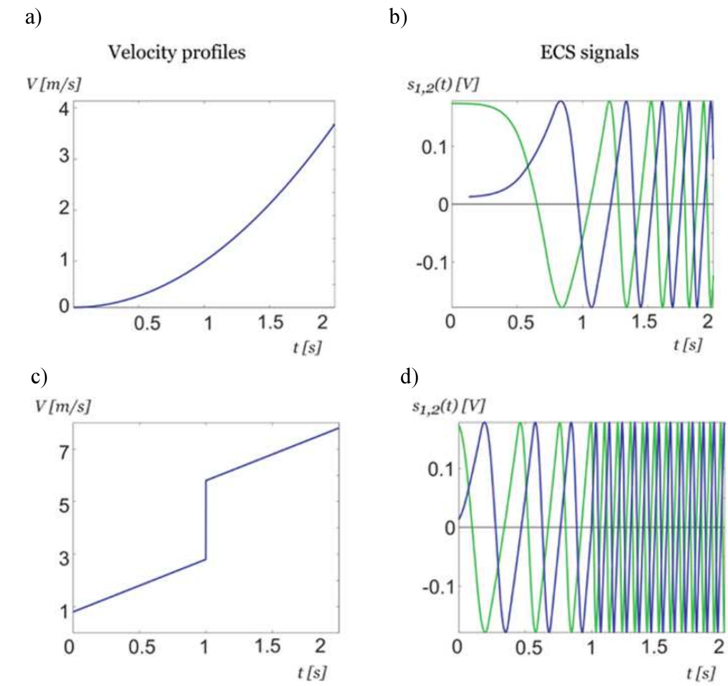

Fig. 7. The simulated ECS signals; (a) and (c) show the simulated velocity profiles; (b) and (d) show the corresponding signals of two sensor coils without additive noise.

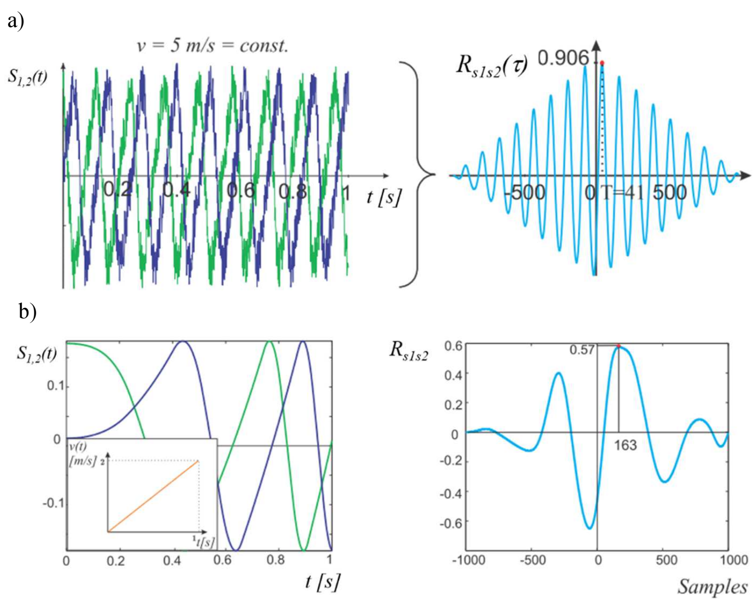

Fig. 8. The qualitative results of the cross-correlation applied to simulated data. The cross-correlation for noisy constant-velocity ECS signals (a); The cross-correlation for a linear acceleration (b).

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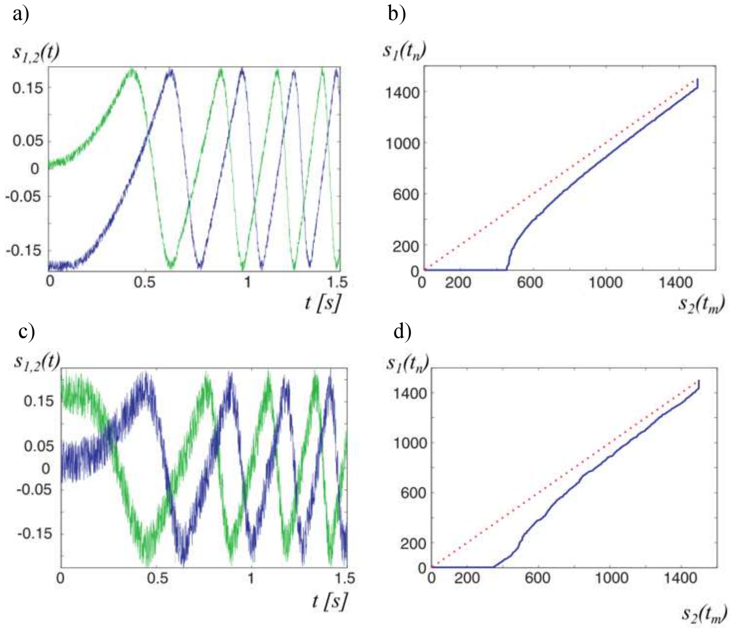

Fig. 9. The simulated results for DTW. The drawings on the left depict the input signals for a constant acceleration with increasing noise; the drawings on the right show the estimated velocity.

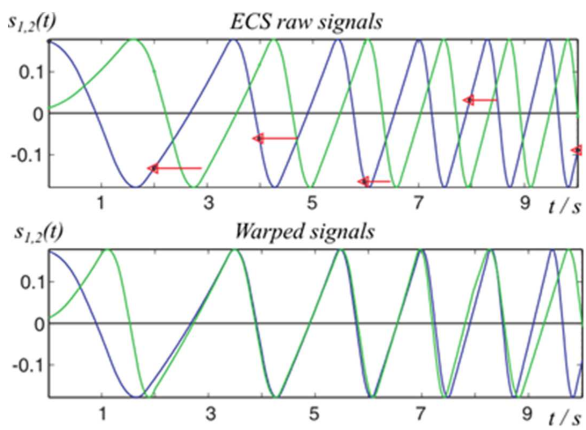

Fig. 10. Simulated result of COW. The upper section shows simulated eddy current signals with accelerations. The arrows indicate the shift of the individual segments. The lower section shows the warped results.

Adding moderate noise does not change the results at all. As the intrinsic cross-correlation quality measure COW is much more robust against additional noise than the classic DTW. Fig. 11 shows the results for noisy signals at a constant acceleration and clearly demonstrates capabilities of the approach.

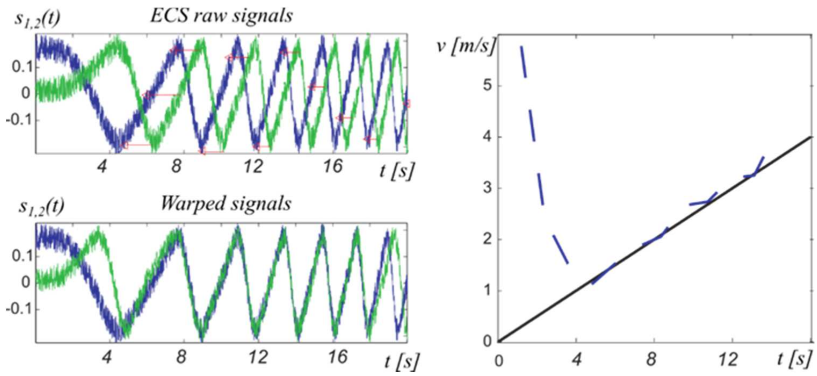

Fig. 11. The simulated results for COW given noisy signals with a constant acceleration. The left section shows the input and warped signals; the right section shows the estimated velocity in the segments as a dotted line and the correct profile as a solid line.

Summary: The results clearly indicate usefulness of the COW algorithm as compared to the DTW algorithm and the classic cross-correlation. It is robust against noise and can deal with an acceleration within the interval. As a drawback it should be mentioned that the computational load largely exceeds that of the cross-correlation.

Table 1 gives a qualitative overview of the obtained results.

Table 1. Qualitative Comparison of the simulated data.

	Complexity of computation	Robustness against noise	Precision v = const. / ≠ const.
CLC	++	+	+ / -
DTW	-	--	+ / --
COW	--	+	+ / +

5. Experimental results

The algorithms were also used for real-world data obtained during test drives on a tram. Fig. 12 shows an experimental signal sample and the resulting velocity estimates for CLC and DTW. The cross-correlation approach shows good estimation behaviour. The signal jumps marked in Fig. 12c correspond to abrupt velocity changes in estimation and indicate a low applicability to real-world scenarios, where a more reliable and smooth result is needed.

On the other hand, COW could solidify the expectations based on the simulated data, showing a good overall noise reduction and reliable and smooth velocity estimates even in areas with high accelerations. This is shown in Fig. 13 for a sequence with a nearly constant velocity (a) and a sequence for a starting train in a station (b). The signals align well in both scenarios and exemplify the quality of the velocity estimation. The results at constant velocities are 4.14 m/s for CLC and 4.42 m/s for COW, which principally proves applicability of the warping algorithm. To cite quantitative results for areas with higher accelerations an additional velocity sensor is necessary, as the classical CLC fails to deliver comparable true ground data.

The results obtained with the experimental data correspond mostly with the results of the simulation. An exception is the DTW performance, which shows a strong decrease in precision when compared to the simulation and other methods.

The results clearly indicate that COW is an alternative to the common CLC-based velocity estimation, especially at low velocity manoeuvers. A drawback is its high computational load.

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Intermediate results cannot be calculated in advance and up to several seconds are needed, even for small sequences. This makes the presented algorithms less capable for online systems than the model-based approaches recently presented in [23] and [24]. Nonetheless, as proposed in our system setup in Fig. 1, the warping-based estimate needs only to be calculated below a certain velocity threshold or can be used to get precise velocity results in an offline mapping step. As a rough initial estimate is given by CLC, one can even optimize the necessary segment length to make the computation feasible. This could spread capabilities of the ECS system for additional low-speed use cases like turnout detection and classification, which were proposed in [25].

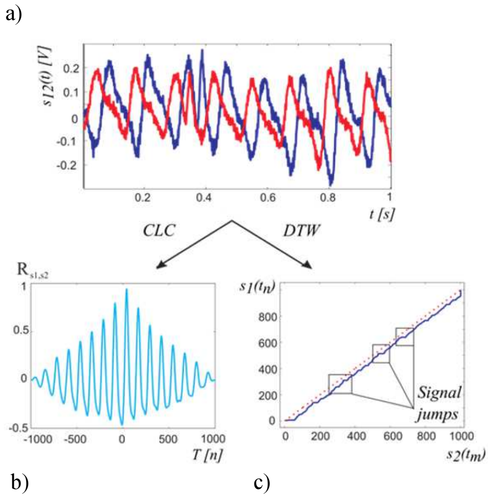

Fig. 12. CLC (b); DTW (c); results for the experimental data (a).

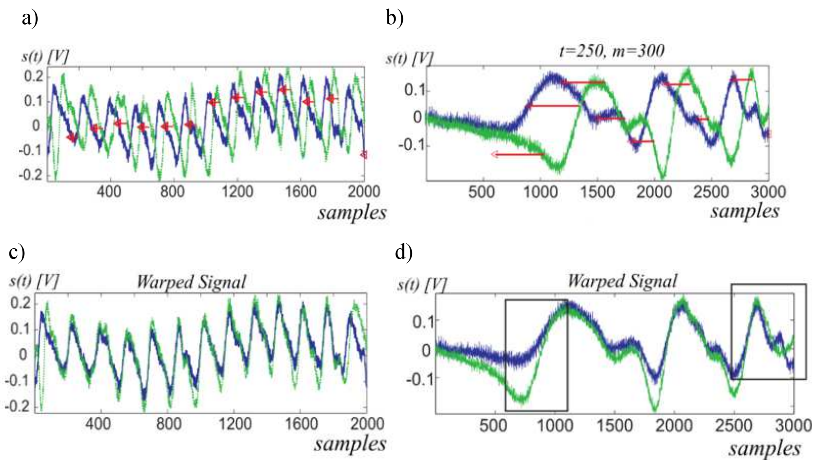

Fig. 13. The results for COW with the experimental data. (c) shows the warped signal from (a) at a nearly constant velocity. (d) represents the situation at a high acceleration for the input signal (b).

6. Conclusion

This paper proposes a novel approach for determining the signal shift of ECS signals for the purpose of velocity estimation. Dynamic time warping and correlation-optimized warping were described. They may be applied in an additional pre-processing step for precise rail vehicle velocity estimation in low-speed scenarios. The important conclusion is that simple signal warping should be handled with care. One must bear in mind that the classical DTW was originally proposed for pattern recognition tasks and is not robust to noise or larger signal variations. COW copes much better with the given challenges in heavy-duty train operating systems. We have qualitatively and quantitatively demonstrated that a good velocity estimate in low-speed and high-acceleration scenarios is possible.

The proposed system chooses an algorithm based on the current velocity. The fast and reliable CLC estimate is used in areas with a low acceleration, whereas the COW one is incorporated when the rail vehicle either starts or comes to a halt.

COW is not particularly sensitive to the exact choice of parameters, although maximum segment and slack lengths should not be exceeded to ensure quality. Due to a relatively small search space, the trial and error approach for choosing the optimal settings is feasible even on modest computer systems. Further work could examine the best parameters and additional speeding up of the algorithm.

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